EVALUATING PERFORMANCE OF PEER-TO-PEER LENDING PLATFORMS: A CROSS-COUNTRY EMPIRICAL STUDY OF PANEL DATA

A thesis submitted by

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Abstract

It has been a decade since crowdfunding and peer-to-peer (P2P) lending opportunities were first created. Today, an overwhelming number of P2P lending platforms can be found in both developed and emerging economies. A better understanding is needed not only of the dynamics of successful P2P lending, but also of the use and distribution of P2P lending mechanisms. This PhD study empirically investigates the main macroeconomic, country-related and borrower-specific factors influencing the credit risk in the P2P lending market via the utilisation of panel data regression analysis. The study investigates the impact of the interest rate and inflation on borrower-level loan delinquencies. By aggregating regional- and country-level data from the loan books of multiple platforms, this study examines the factors related to the default risks of loans issued by P2P lending platforms. The results indicate that a higher interest rate and inflation increase the probability of default in the P2P lending market. The positive association between inflation and interest rate on the probability of default is more pronounced when regional- and country-level religiosity and borrower ratings are lower. The results are robust to endogeneity correction and several additional analyses. This study also provides early evidence of the COVID-19 pandemic-induced exposure to liquidity risk in the P2P lending market. This study examines the listings in Bondora's Secondary Market (Estonia), indicating that, despite increased volatility, the probability of success increased during the period of the pandemic. The outcomes of this study are applicable in regional and cross-country diversification of P2P lending, as is the case in traditional finance, paving the way for the market's future best practices.

Keywords: peer-to-peer lending, crowdfunding, default, marketplace lending, panel data, COVID-19, coronavirus, liquidity risk

Certification of Thesis

This thesis is entirely the work of Asror Nigmonov except where otherwise acknowledged. The work is original and has not previously been submitted for any other award, except where acknowledged.

Principal Supervisor: Professor Khorshed Alam

Associate Supervisor: Dr Syed Shams

Student's and supervisors' signatures of endorsement are held at the university.

Dedication

I dedicate this study to the spirit of both of my grandmothers who are no longer in this world.

Thank you so much "Kotta oyi" and "Aya".

Acknowledgements Statement

I show my sincere gratitude to my parents, family members and friends who have been uninterrupted source of sustain for me while enduring the tribulation of this work.

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Table of Contents

List of Figures

List of Tables

Abbreviations

€	euro/s
ASIC	Australian Securities and Investment Commission
CPI	Consumer Price Index
DTI	debt-to-income
ESI	Economic Sentiment Indicator
EU	European Union
FCA	Financial Conduct Authority (UK)
FE	fixed effects
FICO	Fair Isaac Corporation
GDP	gross domestic product
GFC	Global Financial Crisis
GMM	generalised method of moments (estimation)
IPO	Initial Public Offering
ISA	individual savings account
IT	information technology
IV	instrumental variable
LSDV	least-squares dummy variable
NPLs	non-performing loans
OECD	Organisation for Economic Cooperation and Development
OLS	ordinary least squares
P2P	peer-to-peer
PD	probability of default
RE	random effects
SMEs	small and medium-sized enterprises
SSE	Shanghai Stock Exchange
UK	United Kingdom (of Great Britain and Northern Ireland)
US/USA	United States/United States of America
WHO	World Health Organization

A bank is a place that will lend you money if you can prove that you don't need it.

— Bob Hope (1903-2003)

Chapter 1: Introduction

1.1 Background of the topic

It has been a decade since crowdfunding and peer-to-peer (P2P) lending[1] opportunities were first created. Today, an overwhelming number of P2P lending platforms can be found in both developed and developing economies. Studies of P2P lending practices promote the diverse possibilities of transferring best practices and promoting new methods of financial lending. In a growing number of studies, researchers are taking a direct look at P2P lending platforms, but most studies are based on theoretical grounds rather than having an empirical foundation. Prior studies largely lack empirical investigation in their observation of the current trends and main factors influencing the growth of P2P lending. Moreover, contradictions or similarities between traditional theories of finance and P2P lending mechanisms are largely ignored in the literature. A better understanding is needed not only of the dynamics of successful P2P lending, but also of the use and distribution of P2P lending mechanisms. This study, in reflecting on the gap in the existing literature, aims to explore the P2P lending practices from the perspectives of the P2P platforms.

This introductory chapter is structured in the following order. Section 1.2 explores the notion of P2P lending and identifies its importance. Section 1.3 highlights the current state of the industry and contemporary developments. Section 1.4 provides the statement of the research problem, the research questions and the objectives. Section 1.5 presents the study's motivation and its scope. Section 1.6 identifies the foundations of the study and introduces the conceptual framework. Throughout this section, the author uses the prior theoretical literature to explore the arguments to related this topic. The final two

[1] Also referred to as "lending-based crowdfunding", "marketplace lending", "crowdlending" and "loan-based crowdfunding".

sections (Sections 1.7 and 1.8) of this introductory chapter outline the study's contributions and the structure of the thesis, respectively.

1.2 Defining peer-to-peer (P2P) lending and its importance

The decade following the Global Financial Crisis (GFC) has seen a significant surge in alternative lending practices. Among these lending practices, P2P lending has transformed worldwide into a new channel for entrepreneurial start-ups in securing much-needed funds (Oren, 2013; Zhang, Baeck, Ziegler, Bone, & Garvey, 2016). In this regard, access to funds is not accompanied by venture capital or other traditional sources of venture investment. Online P2P lending platforms mostly match supply and demand for funds, thus allowing individual lenders to aggregate their funds to finance loan requests from individuals and businesses. The distinguishing feature of P2P lending that brought its widespread popularity is the removal of intermediaries. As in any other loan agreement, the lender is responsible for lending capital over the term of the loan, while the borrower commits to repaying this capital with interest in accordance with the loan agreement. However, unlike banks or credit unions, P2P platforms only help to facilitate the transaction by performing a credit assessment on the borrower and matching borrowers to lenders. As a result, P2P lending is a direct loan contract between lender and borrower in which the P2P platform is solely a facilitator. Consequently, these platforms emerged as an innovative means of financing in terms of their capacity to remove intermediaries from traditional lending practices. As these platforms offered attractive and predictable returns, they attracted yield-hungry investors keen to diversify their portfolios with alternative investments.

In its essence, P2P lending is regarded as a debt-based form of crowdfunding (Cumming & Hornuf, 2018). The concept of crowdfunding is motivated by the notions of crowdsourcing and microfinance and is based on the prior work of Morduch (1999) and Poetz and Schreier (2012). It is generally perceived to be a distinct type of funding accessed by fundraisers via numerous internet sites devoted to the topic (Poetz & Schreier, 2012). According to Schwienbacher and Larralde (2010), crowdfunding can be defined as an internet-based call for funds to support initiatives for a specific purpose, either in the form of a donation or in exchange for some form of reward. These various definitions of crowdfunding, however, ignore certain types of investment that were also classified as 'crowdfunding' in the mainstream literature. Thus, crowdfunding may embrace lending practices such as internet-based P2P lending (Lin, Prabhala, & Viswanathan, 2013) or fundraising attempts launched by a dedicated group, such as fans of music groups (Burkett, 2011). However, the current study adopts the definition of Agrawal, Catalini and Goldfarb (2011) which states that 'crowdfunding' is initiated for cultural, social and for-profit reasons by collecting small contributions from numerous individuals, with the whole process not involving any intermediaries and using internet platforms to make the connections between lenders and borrowers. The debt-based form of crowdfunding practices, in turn, is classified as P2P lending. Based on the above definition, the next section of this thesis explores the current state of the P2P lending industry. It should be noted that P2P lending is in its initial stage of development and that various prior studies have referred to all forms of crowdfunding. This study, as it progresses, refers to all forms of crowdfunding in the review of the prior literature and model building.

1.3 State of P2P lending industry

An overwhelming number of P2P lending platforms are in operation worldwide. In the European Union (EU) countries, 79 platforms have successfully raised around € (euros) 16.8 billion since 2010 (ORCAMoney, 2017). Tomlinson, Foottit and Doyle (2016) reported a cumulative annual growth rate of 87.4% for the European market and 109.4% for the United Kingdom (UK) market between 2010 and 2015. The USA P2P lending market accounted for over US$2 billion in 2018, a 40% increase from 2017 (CCAF, 2020). In the Asia-Pacific region, the main share of the market is attributed to China. The alternative finance market in China was almost non-existent before 2010, but by 2015, had reached a staggering loan volume of US$101.7 billion (Zhang et al., 2016). The contribution of other countries in the Asia-Pacific region, including Australia, is small. The total market volume of the Australian alternative finance market amounted to US$348.4 million in 2015. However, the growth in the Asia-Pacific market from 2014–2015 was over 300% (Zhang et al., 2016).

Despite its high growth rates over the past few years, P2P lending still represents a small fraction of total bank lending. Even in the UK, where P2P lending has the most rapid development, it accounts for 0.53% of total unsecured consumer lending and 0.45% of total small and medium-sized enterprise (SME) lending (Milne & Parboteeah, 2016). Moreover, the impressive growth of this market indicates a favourable business environment, rather than the strength of P2P lending markets. The industry has been sailing in safe waters since the GFC with low interest rates and generally stable economies worldwide.[2] Although the growth rates look impressive, the future of the industry is still uncertain, as it largely depends on complex and interrelated macroeconomic factors (J. Li, Hsu, Chen, & Chen, 2016). Tomlinson et al. (2016) admitted that the interest rate environment alone may lead to an expected divergence in the penetration of P2P lending in the UK market from £0.5 billion (under a normalised interest rate environment) to £35.5 billion (under the current interest rate environment) by 2025.

This industry also has several potential risks that pose threats to investors and to the P2P platforms themselves. These risks include factors such as the variability of defaults, loan recovery, platform failure, fraud or cybercrime (Milne & Parboteeah, 2016). In this regard, the industry already discloses a high level of information that provides transparency to mitigate the risk factors incurred by investors. Diversification across many borrowers substantially protects against the variability of defaults (Bessière, Stéphany, & Wirtz; Cumming & Hornuf, 2018). What remains unprotected over the business cycle are loan loss and default risks. Losses are expected to increase substantially over a major economic downturn which could easily exhaust investors' funds (Bolt, de Haan, Hoeberichts, van Oordt, & Swank, 2012). Accordingly, it is evident that the exploration of loan loss and default risks under different economic conditions and across countries is an urgent need.

Most of the existing literature has ignored the country-related and platform-specific aspects of the P2P lending industry. Most of these studies, as highlighted in the literature review in Chapter 3, lack cross-country empirical analysis and do not compare the differences between countries over time. The existing theoretical perspective supports the impact of country-related variables on financial market performance. However, hardly any research has been conducted that specifically highlights the impact of

[2] The COVID-19 pandemic has had a detrimental impact on the P2P lending market, as it has on other sectors of the economy. The current study's exploration of the COVID-19 pandemic's impact on this sector is reported in Chapter 7.

macroeconomic factors, and especially of these variables in the empirical analysis of the risk factors of P2P lending.[3]

In realising the importance of the P2P industry, this study formulated the research objective and questions detailed in the next section. The rationale behind the objective and questions is elaborated in later sections of this thesis.

1.4 Research objective and questions

The main objective of this study is to examine macroeconomic, country-related and borrower-specific determinants of P2P lending quality. This study places specific emphasis on the impact of inflation and the interest rate on P2P platforms' credit risk. The following research questions are explored:

1. What are the main country-related and borrower-specific determinants of P2P loan defaults?
2. What is the association between the regional inflation and interest rate and P2P loan defaults?
3. What is the association between the country-level inflation and interest rate and P2P loan defaults?

The current study reviews the P2P lending literature and investigates the primary macroeconomic variables with the potential to contribute directly to the growth of this industry, as well as the risk factors faced by both lenders and borrowers. The study places specific emphasis on the impact of cross-country and regional differences by exploring their association with loan defaults in the regions and countries under consideration.

Through collecting and compiling a platform-level unique data set covering the period from 2008–2019, this study conducts a cross-country empirical analysis to investigate the effect of macroeconomic, country-specific, borrower-specific factors on P2P lending practices and risk factors associated with these lending platforms.

As the research within this study's framework progressed in the dynamic industry of P2P lending, it experienced unprecedented hurdles. In relation to the economy and the financial sector, the COVID-19 pandemic had a detrimental impact on the P2P lending

[3] The supporting theoretical and empirical evidence is provided in the literature review in Chapter 3 of this thesis.

market. It is not yet possible to assess the full impact of the pandemic-induced economic downturn on P2P lending. However, the author believes that this study's results, as they relate to the impact of macroeconomic variables on the P2P lending market, might be extremely useful for P2P market participants. Reflected on this changing external environment, the current study undertook additional effort to explore the early impact of the pandemic on the P2P lending market liquidity risk. Thus, Chapter 7 of this thesis presents the study's exploration of the following research question:

4. What is the impact of the COVID-19 pandemic on liquidity risk in the P2P lending market?

1.5 Scope of the study

This study's scope is limited by the availability of the necessary data. It covers only those countries that currently have operating P2P lending markets, that is, the United States of America (USA) and EU member countries as they have had established P2P lending markets for more than 10 years and are similar in terms of their economic development. These inclusion criteria make it possible for data to be available for analysis, with appropriate comparisons able to be made between the P2P markets in these countries. Developing countries, such as China, also have operating P2P lending markets with data available for more than five years. However, the inclusion of developing countries would largely distort future analysis and overextend the study's scope. Therefore, the scope of this study is limited to developed countries (namely, EU countries and the USA) and excludes developing countries, such as China, from the analysis.

1.6 Conceptual framework

To guide this study's empirical investigation of the P2P lending market, a conceptual framework is developed based on asymmetric information theory. It is noted that P2P lending platforms face the same set of obstacles in assessing the creditworthiness of borrowers. As P2P lenders coexist with banks, their loan assessment practices are not stringent compared to those of traditional financial institutions. This feature of P2P lending allows it to expand its borrower reach beyond that of banks and to offer attractive investment opportunities. This same feature further inflates the problem of asymmetric information and increases the borrower credit risk. The following subsections first compare banks with P2P lending platforms in terms of their borrower screening. They next explore how these differences translate into credit risk and changes in the interest rate. The framework derived by this study links the probability of default with determinants based on asymmetric information while considering the specifics of P2P lending markets.

1.6.1 Traditional banking versus P2P lending

Online P2P lending platforms are prominent by-products of the development of electronic markets. Peer-to-peer (P2P) lending is defined as a practice which involves lending microloans to individuals by only introducing borrowers to lenders through an online marketplace (Cumming & Hornuf, 2018). In its early years of development, the P2P lending market was also called a ‘microlending market’ as the number and amount of loans issued by these platforms were small (Emekter, Tu, Jirasakuldech, & Lu, 2015). However, loans in P2P lending markets fundamentally differ from any form of microlending provided by traditional financial institutions. Banks have traditionally acted as intermediaries between savers and borrowers, collecting deposits which are used to fund lending. Traditional banking involves people borrowing loans with a low-interest rate from banks. In the case of banks, loan applications are accepted in accordance with borrower characteristics such as having a stable job, enough disposable income and a good credit score. Banks might also ask borrowers to provide some form of collateral, such as their property.

Peer-to-peer (P2P) lending emerged as a means of sidestepping banks by directly matching lenders and borrowers via the internet. A key distinction between P2P lenders and banks is that the former neither accept deposits nor make loans. Thus, P2P lending markets act according to a different set of rules when it comes to screening borrowers. The P2P lending platforms have borrower entry requirements that are comparatively lower than those of traditional banks. Borrowers can easily enter the market without providing financial reports to the extent that they would usually do in bank lending. At the nascent stage, borrowers could directly interact with lenders, hence the term ‘peer-to-peer’ lending. However, this form of lending has evolved to the extent that institutional investors tend to invest in loan bundles; consequently, it is also commonly referred to as ‘marketplace lending’ in the United States (US). According to Weiss, Pelger and Horsch (2010), it is difficult for lenders to evaluate the creditworthiness of borrowers due to both sides meeting anonymously through the internet. Furthermore, due to the low entry requirements, P2P lending markets have shorter processing times.

In the traditional market, information about the creditworthiness of borrowers is provided in substantial detail to the lenders (banks), in comparison to the practice of P2P lending markets. At the same time, banks charge a lower interest rate as the traditional market is safer than the P2P lending market. The P2P lending platforms can be viewed as a 'marketplace' that sells notes matching borrowers with lenders. As this 'marketplace' has less screening and entry requirements, interest rates are accordingly higher in comparison with banks. The P2P lending platforms instead reduce the inherent risk of default by dividing lenders' funds into smaller distinct tranches. These tranches represent the procedure of 'embedded securitisation' as in traditional finance and ensure that funds are lent to many borrowers with varying risk profiles (Deku, 2017). This model manages credit risk by diversifying lenders' investments across several borrowers (Tomlinson et al., 2016). As documented in the traditional financial literature, this form of securitisation may create the problem of 'strategic adverse selection' on the part of lenders (Keys, Mukherjee, Seru, & Vig, 2010; Mian & Sufi, 2009). In this regard, the evaluation of the credit risk of borrowers by P2P lending platforms is fundamentally important for their performance.

1.6.2 Assessment of credit risk in P2P lending

Credit risk evaluation is in its infancy in the P2P lending literature. For instance, studies by Hu and Yang (2014) and Shi and Guan (2016) have neither employed an empirical modelling framework nor have they conducted extensive cross-country analysis in their research on the P2P lending industry. These studies used theoretical frameworks from traditional finance and borrowed concepts from venture capital and angel investments. Lukkarinen, Teich, Wallenius, and Wallenius (2016) raised the importance of this approach, drawing on the usefulness of research from adjacent funding industries for evaluating the performance of alternative investment practices.

The current study utilises asymmetric information theory to investigate the credit risk in P2P lending markets. Thus, the theory of asymmetric information plays a central role in identifying the impact of various determinants on the probability of default, with this related to the three research questions of this study. Most research papers on P2P lending have referred to the theory of asymmetric information as the backbone of interest rate and funding success determination. For example, Akerlof (1970) suggested that information asymmetry refers to signalling as the mitigation mechanism for information failure. In alternative financing markets such as P2P lending, signalling is very important, as each platform brings together complete strangers in financing activity. Signalling theory has been widely examined from the perspective of investors in terms of the determination of interest rates and funding success for borrowers in P2P lending platforms (Freedman & Jin, 2017; Lin & Viswanathan, 2016; Wei & Lin, 2016). However, no study has explored P2P lending platform success from the perspective of information asymmetry. To ensure efficient and sustainable financial intermediation, P2P lending platforms need to ensure that they are not subject to principal–agent problems. The possibility of better assessment of credit risk can decrease the possibility of P2P lending platform failures.

1.6.3 Interest rate and the probability of default

After the GFC of 2007–2008 and as a result of the higher level of regulations that followed, banks set higher standards of lending. The P2P lending industry expanded outside these stringent regulations and more than doubled in size in China, the US and the UK between 2010 and 2014 (Aveni et al., 2015). The rise of the P2P lending market is often attributed to the regulation of traditional bank lending after the GFC, while its growing problem has been the credit default risk as a result of information asymmetry (Emekter et al., 2015). Lenders are not informed about the risks and borrowers' credit conditions to the extent of borrowers' knowledge about themselves. Once the transaction has taken place, lenders may not be able to observe borrowers' actions, project return or duration, or be able to force borrowers to repay loans (ex-post asymmetric information problems) (Jaffe & Stiglitz, 1990). As borrowers only negotiate with lenders in an online environment and do not meet face to face, it is difficult for lenders to know the credit information and debt status of borrowers (Weiss et al., 2010).

To summarise the information asymmetry outcomes in P2P lending markets, both lenders and P2P lending platforms cannot adequately monitor the real purpose and loan behaviour of borrowers. Following Akerlof (1970) and Greenwald and Stiglitz (1987), these situations might lead to adverse selection and moral hazards. In this case, asymmetric information allows insolvent borrowers to enter the market (a moral hazard).

Investors, being unaware of borrowers' insolvency, might grant loans to these borrowers (adverse selection) and increase the credit risk. With the increased credit risk, the P2P lending platform raises its average interest rates to maintain the rate of return required by investors. Higher interest rates drive away solvent borrowers (due to the rise in borrowing costs), thus increasing the probability of default. With solvent borrowers exiting the market, the ratio of insolvent borrowers to solvent borrowers increases, further adding to the problem of asymmetric information, as illustrated in Figure 1.1 below.

As it is highlighted in Figure 1.1, moral hazard and adverse selection are the direct consequences of information asymmetry. These problems, in turn, increase the credit risk incurred by market investors. Thus, based on the theory of asymmetric information, the average interest rate plays a central role in credit risk assessment by determining the probability of default. Peer-to-peer (P2P) lending platforms mostly offer investors a basket of loans based on automated algorithms or investors' individual preferences. As a result, investors are exposed to the risk of an average borrower in this basket, rather than the risk of the individual borrower.

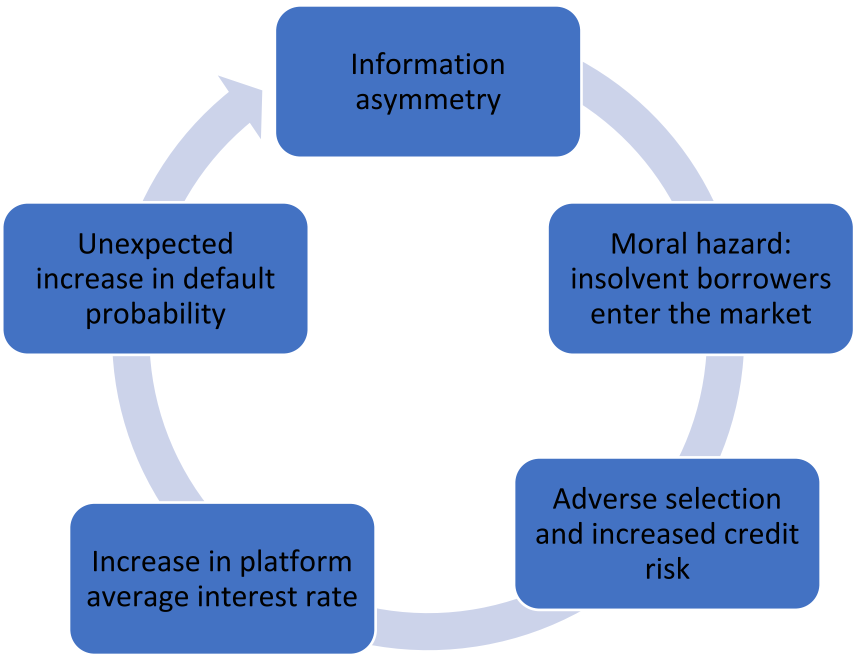

Figure 1.1: Asymmetric information and probability of default

1.6.4 Inflation and probability of default

Drawing on insights from asymmetric information theory, a number of models have included possible scenarios where macroeconomic variables, such as inflation, affect the net worth of potential borrowers (Bebczuk, 2003). When the asymmetric information problem arises, it causes the ‘financial accelerator’ effect, although the relationship might be complicated and highly intractable (Bernanke, Gertler, & Gilchrist, 1998). The strategy adopted by researchers has been to use one particular formulation of asymmetric information problems as being representative of all scenarios and to assume *a priori* whether or not those problems are solvable. As a result, different models have different formulations of agency costs and the external finance premium.

The growing theoretical literature describes mechanisms whereby even predictable increases in the rate of inflation interfere with the ability of the financial sector to effectively allocate resources. More specifically, recent theories emphasise the importance of informational asymmetries in credit markets and demonstrate how increases in the rate of inflation adversely affect credit market frictions with negative repercussions for financial sector performance and, therefore, for long-run real activity (Huybens & Smith, 1998). The common feature of these theories is that informational friction is viewed as having an endogenous level of severity. Given this feature, an increase in the rate of inflation drives down the real rate of return not only on money but also on assets in general. The implied reduction in real returns exacerbates credit market frictions. As these market frictions lead to the rationing of credit, as inflation rises, credit rationing becomes more severe. As a result, the financial sector makes fewer loans, resource allocation is less efficient, and intermediary activity diminishes, with adverse implications for capital investment. The reduction in capital formation negatively influences both long-run economic performance and equity market activity, where claims to capital ownership are traded (Boyd, Levine, & Smith, 2001). Thus, asymmetric information creates a circle of causations from the real economy to the financial sector and around to the real economy again. Further theoretical and empirical evidence in support of using interest rate and inflation as determinants of the probability of default is provided in Chapter 4 ‘Data and Methodology’. The role of these determinants in the analysis of credit risk is also discussed in the same chapter.

1.6.5 Macroeconomics and probability of default

In its analysis of credit risk in P2P lending markets, this study uses a range of control variables to represent various factors that affect credit risk. In this regard, financial accelerator and life-cycle consumption theories are prevalent in traditional finance to relate country-specific variables to loan volumes and defaults. Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) applied financial accelerator theory in their studies of traditional financial markets and posited that borrowing becomes more difficult and expensive during a recession owing to increased external finance premiums. On the other hand, life-cycle consumption theory directly relates business cycles to financial intermediation and states that the ability to default when income is low allows people to borrow against an uncertain future (Lawrance, 1995). These enhanced levels of borrowing increase consumption rates and borrowers' debts (Lawrence 1995). Gompers and Lerner (1998) and Félix, Pires and Gulamhussen (2013) empirically tested these theories in alternative investment markets by proposing that stock market development, growth in the gross domestic product (GDP) and unemployment have an impact on the development of venture capital investments. Variables prevalent in these models, such as GDP growth, are further explained in Chapter 4. Another group of studies related entrepreneurship to economic development. Studies by Acs and Szerb (2007), Armour and Cumming (2006) and Cumming, Johan, and Zhang (2014) stated that countries with higher economic growth tend to have a more advanced entrepreneurship environment. Later papers on venture capital investments, such as that of Groh and Wallmerokh (2016), documented the same proposition. The conceptual framework of the current study is drawn from these concepts. It is expected that countries with higher economic and business environment indicators will have larger volumes of P2P loans and, accordingly, higher aggregated loan defaults.

Therefore, this study uses financial accelerator, life-cycle consumption and asymmetric information theories, all of which have been extensively tested in traditional financial markets (and in alternative investment markets to a lesser extent), to motivate the key research questions, as proposed in section 1.4. Using these theories, this study investigates the macroeconomic and borrower-specific aspects of P2P lending markets from the perspective of their respective impact on loan quality and credit risk.

The above-highlighted factors, based on the review of the literature, form the backbone of analysis in this study. Thus, while formulating the research instruments, these determinants are duly considered for gaining an understanding the credit risk and for drawing recommendations, as reflected in the study's objective. The conceptual framework, highlighting various factors that affect the credit risk and, consequently, the probability of default, is summarised in Figure 1.2. In this regard, inflation and interest rate are expected to impact on the probability of default when reported in the empirical chapters of this thesis. This study uses indicators representing borrower characteristics, macroeconomic factors, the business environment, politics, demographics and technology as control variables in the regression analyses reported in Chapters 5, 6 and 7. Inclusion of a broad range of indicators, extending beyond borrower characteristics, is one of the unique aspects of the current study with wide implications for policy, business and theoretical considerations.

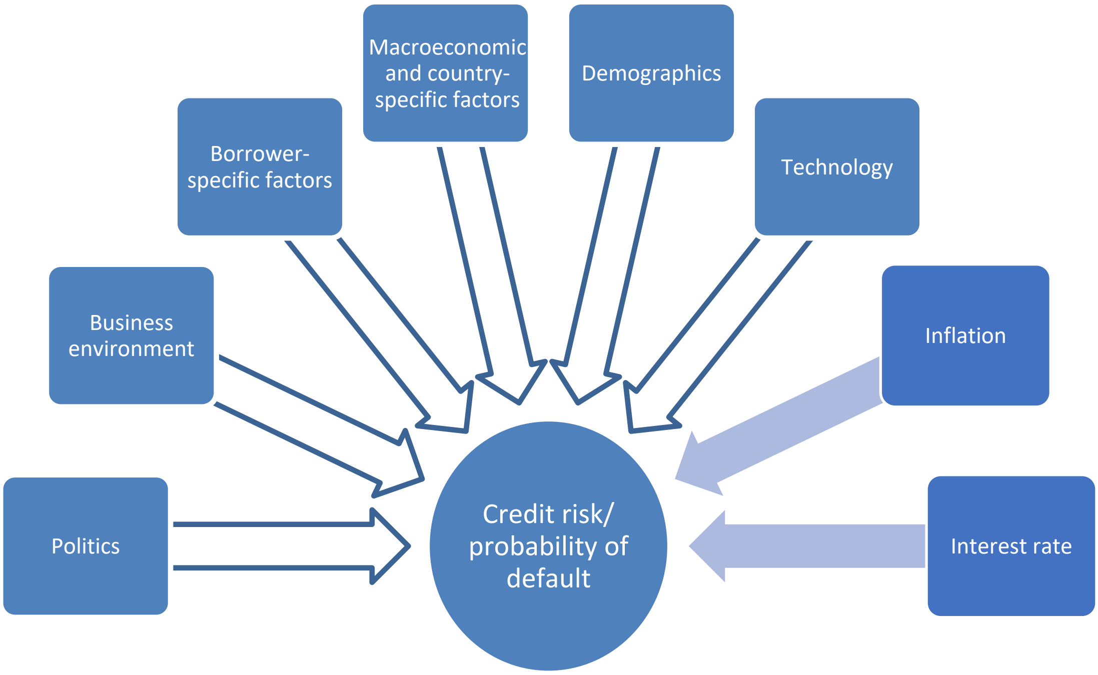

Figure 1.2: Conceptual framework of factors affecting credit risk/probability of default

1.7 Contributions of the study

As it is indicated earlier in this chapter, the number of existing studies is very limited in terms of the use of empirical analysis. Prior literature investigates specific tendencies and factors influencing P2P lending in a limited context. For instance, no studies appeared to have sought an understanding of the dynamics of successful P2P lending or of the use and distribution of P2P lending mechanisms. Moreover, scholars have not sought existing contradictions or similarities between traditional theories of finance and P2P lending mechanisms (Tan, Shao, & Li, 2013). Therefore, as crowdfunding and P2P practices continue to develop along with their complementary policies, an urgent need has emerged for empirical investigations of this topic with appropriate reference to existing theoretical understandings.

Accordingly, this study makes a considerable contribution in terms of its implications for methodology, theory and policy. Firstly, this study enables the quantification of risks and the analysis of risk factors related to business cycles in the P2P lending market. Thus, it fills the gap in the existing literature by developing a cross-country model that is then tested via econometric analysis. Secondly, this study proposes a new P2P lending platform management framework to overcome or control various risk factors in the P2P lending market, taking into consideration country-specific factors. Thirdly, based on its findings, the research highlights several policy implications by identifying the potential for the development of the P2P lending market in specific countries. At the same time, based on the identified risk factors, the study proposes that specific recommendations be made to governments to allow the full exploitation of the existing potential of this industry. In this respect, more regulations and privileges could be introduced that may enhance the market's efficiency. Fourthly, as P2P lending has been developing on its own without the economy having any effect, evidence of the relationship between economic variables and P2P lending is expected to be vital for this industry's further development. Based on the same evidence, forecasting mechanisms may be put in place to mitigate risk factors in a way that was not previously possible. Fifthly, this study's findings make a significant contribution to investors' understanding of the P2P lending method and allow the realistic management of expectations. Finally, the study reveals the degree of individual specificity and heterogeneity of each state and country under consideration, with these factors possibly having a substantial impact on their competitiveness. This level of heterogeneity with its own specificity could be further considered in a policy setting. In summary, the study's subsequent outcome could be a theoretical model of cross-country diversification for P2P lending, in line with that of traditional finance. This model, in its turn, could pave the way for future best practices and sufficient growth of the market.

1.8 Organisation of the thesis

This thesis is structured in the following order:

Chapter 2 begins with an explanation of the economics of, and rationale behind, the emergence of P2P lending practices. The chapter reviews and discusses the methods used by P2P lending platforms to assess and mitigate credit risk. In Chapter 2, current trends and challenges faced by the industry are discussed. The chapter also discusses the current regulatory environment faced by P2P lending platforms in the USA and Europe.

Chapter 3 reviews the existing theoretical and empirical literature on P2P lending. As only a limited number of studies are available in the literature on P2P lending practices, the study refers to the related literature on traditional and alternative finance, if applicable. This chapter also highlights the limited studies in the literature on the determinants of P2P lending. Chapter 3 then formulates the hypotheses, with this process mostly based on the available theoretical and empirical literature in traditional finance. Considering the recent changes in external market conditions, Chapter 3, in a separate section, explores the impact of the COVID-19 pandemic on the financial sector.

Chapter 4 begins by explaining the significance of the theoretical and empirical studies in drawing this study's model and highlights the model's specific features. The chapter explains the features of the data used for the model. The technical aspects of the study are explained in more detail. Chapter 4 covers important issues such as the philosophy of the research, the study's methods, the data collection procedure, aggregation of the data set and the sampling decision. The chapter expands on the conceptual framework and further elaborates on factors affecting credit risk in the P2P lending market. Furthermore, it describes the main variables and regression models in accordance with the developed hypotheses, as presented in Chapter 3.

Chapter 5 discusses the results from the study's first set of empirical analysis. It mainly emphasises the macroeconomic determinants of loan defaults in the P2P lending market. The results elaborated in this chapter are from the empirical analysis using the loan book data from LendingClub (USA). The panel data set presented in Chapter 5 is aggregated as monthly data for each individual US state.

Chapter 6 is built on the results of the second set of empirical analysis that explores the probability of default in P2P lending markets in Continental Europe. The empirical analysis in this chapter is framed around the methods used in Chapter 5 and expands the scope by using a cross-country data set. The study bases the empirical analysis described in Chapter 6 on the loan book data from Bondora (Estonia) and Mintos (Latvia), which includes loan originators from 20 European countries.

In Chapter 7, the study analyses the impact of` the COVID-19 pandemic on the P2P lending market. Chapter 8 presents the concluding remarks, beginning with the extent to which the current study's results comply with existing studies, then the study's policy implications and, finally, the limitations of the current study and the room for further research. The structure of the thesis is visually presented in Figure 1.3.

Chapter 1: Introduction

Background of the study

Research objectives and questions

Conceptual framework

Contribution

Thesis structure

Chapter 2: Institutional Background of P2P Lending

Market origins and current trends

Challenges faced by P2P lending platforms

Regulatory environment

Chapter 3: Literature Review

Review of literature on P2P lending

Related literature on traditional and alternative finance

Hypotheses development

Chapter 4: Data and Methodology

Sample selection

Description of data

Modelling and regression methods

Chapter 5: Macroeconomic Determinants of Loan Defaults in P2P Lending Market: Empirical Analysis Based on LendingClub (USA)

(Empirical chapter)

Chapter 6: Determinants of Loan Defaults in P2P Lending Markets of Europe

(Empirical chapter)

Chapter 7: Impact of`COVID-19 Pandemic on P2P Lending Market

(Empirical chapter)

Chapter 8: Conclusion

Figure 1.3: Organisation of the thesis

Chapter 2:

Institutional Background of P2P Lending

2.1 Introduction

P2P lending has become an innovation in terms of its ability to remove intermediaries from the process. At the same time, the world of modern alternative investments is becoming increasingly complex to navigate. An overwhelming number of P2P lending platforms have been developed during the past decade, making it difficult for any developed economy to remain away from these new financial products. The markets for personal and business loans have been transformed with P2P lending products so popular that governments have created special innovative finance agencies to help consumers to invest in them. Technology has powered the sharing economy, with people now able to connect and rent out everything from their driveways to their cooking. This has enabled consumers to bypass mainstream banks in their quest for funds. Therefore, P2P lenders are expected to secure a strong foothold in the financial sector in the very near future. Considering that P2P lending is a relatively new concept in financial lending, appropriate elaboration is needed of its definitions, as well as a description of early market trends, government regulations and challenges faced by the P2P lending market. Thus, this chapter provides an institutional background to P2P lending, introducing the concept of P2P lending as a new form of capital formation. The chapter first provides a general outline of the definitions and evolution of P2P lending practices. It then highlights the salient differences between different forms of P2P lending and their role in the economy. The chapter next provides an overview of the P2P lending market with specific emphasis on its role in alternative finance. Finally, this chapter explores the social welfare and regulatory aspects of the P2P lending market.

2.2 Defining the basics

Peer-to-peer (P2P) lending is part of the growing industry of alternative lending practices. However, it is a relatively new concept in financial lending and needs proper descriptions drawn that are based on earlier studies. Essentially, it is considered a debt-based form of crowdfunding. The concept of crowdfunding is motivated by the notions of crowdsourcing and microfinance and is based on the prior work of Morduch (1999) and

Poetz and Schreier (2012). Via numerous internet sites devoted to the topic, P2P lending is generally perceived to be a distinct type of funding by fundraisers (Poetz & Schreier, 2012). One of the early studies of Schwienbacher and Larralde (2010) provided initial definitions and understandings of crowdfunding. Using a case study framework, the study demonstrated how a French music crowdfunding start-up emerged in 2007, raising over €50,000. This case study, as one of the early experiments in crowdfunding, highlights several characteristics of, and challenges faced by, crowdfunding and P2P lending practices. These aspects are: (a) possibility of networking; (b) improving the project via feedback loops; but also (c) the considerably low level of funds raised. According to Schwienbacher and Larralde (2010), crowdfunding can be defined as an internet-based call for funds to support initiatives for a specific purpose, either in the form of a donation or in exchange for some form of reward.

However, the various definitions of crowdfunding ignore certain types of investment also classified as 'crowdfunding' in the mainstream literature. Thus, crowdfunding may embrace such lending practices as internet-based P2P lending (Lin et al., 2013) or fundraising attempts launched by dedicated groups such as fans of music groups (Burkett, 2011). A wider definition of 'crowdfunding' has proven elusive, particularly when the term 'crowdfunding' embraces many current and forthcoming practices across various disciplines. Within this study's framework, the author relies on the entrepreneurial context of both crowdfunding and P2P lending. Specifically, this study adopts the definition of 'crowdfunding' which states that it is initiated for cultural, social and for-profit reasons by collecting small contributions from numerous individuals, where the whole process does not involve any intermediaries and uses internet platforms to make the connections between lenders and borrowers (Agrawal et al., 2011).

Lending practices, similar to P2P lending, have been around as one among many non-bank financial intermediaries throughout history. One of the widely documented examples is the notarial credit entities in France that rose to prominence during the 18th century (Hoffman, Postel-Vinay, & Rosenthal, 2019). The working principles of these notaries, such as the loan matching process and information networks, were similar to the current P2P lending platforms. However, banks remained the primary institutional lending party in the economy. With the emergence of digital technologies, such as the internet, big data collection, blockchain cryptography and smart contracts, the previous strengths of centralised financial institutions have been diminished. These new technologies have made P2P lending extremely attractive, contributing to the early rapid growth of the P2P lending market. Through digital technologies and online social networking, P2P lending platforms have simplified the borrower experience and cut the traditional middleman (banks) from the funding flow equation (Cumming & Johan, 2019; Welltrado, 2018). Instead, P2P lending platforms offer end-to-end loan solutions to borrowers and lenders with their active participation.

Compared with traditional bank finance, the role of P2P lending is either as a complement or as a substitute. The original intent of P2P lending platforms might have appeared consistent with the view that P2P lending was a substitute for banks. Traditional financial institutions, such as banks, are able to raise very similar amounts of funds to those raised by current P2P lending platforms. However, P2P lending platforms offer an array of fee arrangements with more variety which might be more attractive than the fee arrangements offered by banks (Cumming & Hornuf, 2017). Traditional forms of finance have been criticised for certain levels of racial and gender discrimination in their offers of financing arrangements (Bellucci, Borisov, & Zazzaro, 2011; Blanchflower, Levine, & Zimmerman, 2003). With their liberal approach and adherence to market mechanisms, P2P lending markets may be less prone to investor bias with respect to age, gender and race (Cumming, Meoli, & Vismara, 2019). Prior studies have found evidence that entrepreneurs have been discouraged from applying for traditional bank finance even when they need credit (van Stel, Storey, & Thurik, 2007; Cole, Dietrich, & Frost, 2019; Cole & Sokolyk, 2016). Based on limited evidence from small business financing, the mechanisms that lead to discouraged borrowers seem to be less pertinent in P2P lending (Cumming & Hornuf, 2017). Substantial evidence is lacking competing interests between banks and P2P lending, but this can be compared to analogous conflicts. Similar conflicts of interest have been seen in technology parks and venture capital, leading them to be regarded as substitutes and not complements (Cumming, Werth, & Zhang, 2019). Likewise, similar evidence has been seen in angel investors and venture capitalists as being substitutes and not complements (Bonini, Capizzi, Valletta, & Zocchi, 2018; Bonini, Capizzi, & Zocchi, 2019; Cumming & Zhang, 2019; Goldfarb, Hoberg, Kirsch, & Triantis, 2013).

However, some empirical evidence is consistent with the view that P2P lending platforms are complements. Specifically, Cole, Cumming and Taylor (2019) provided several arguments defending the view that P2P lenders are actually complements to banks. Firstly, entrepreneurs with fewer sources of potential capital are more likely to be subjected to agency problems that hold them up. Secondly, having capital from one source can serve as a form of external certification that enables capital to be obtained more easily from another source. Thirdly, the community in which an entrepreneur is based is richer if more entrepreneurs are active, as this enables community entrepreneurial agglomeration with respect to more business opportunities, more entrepreneurship and more sources of capital. Cosh, Cumming and Hughes (2009) identified that entrepreneurs typically approach multiple sources when searching for capital and are often turned down by one or more sources. Access to multiple sources encourages more entrepreneurial activity among small businesses than would otherwise be the case. Cosh et al. (2009) investigate the factors that affect rejection rates for different types of investors, including private individuals. Using data from the UK, the authors found that small firms were the ones most likely to obtain financing from private individuals. Therefore, it seems plausible that the advent of P2P lending websites has made it possible for individuals, who otherwise would not have been able to receive a loan from the bank, to obtain the necessary finance through P2P lending to start a business.

2.3 Mechanisms of P2P lending

The working mechanism of the P2P lending model is based on matching borrowers who are seeking a loan with investors. In short, P2P platforms operate by assisting in the collection, scoring and distribution of the credit qualifications of potential borrowers, reporting real-time bids on projects and providing the online servicing and monitoring of the loan. Using this information, lenders have the ability to review loan applications. In general terms, investors may choose to invest algorithmically, directly or through a group. Unlike traditional banks, the P2P lending process involves the direct matching of lenders and borrowers via online auctions in which bid/ask is matched until a loan is fully funded or matched by fixed-rate and category. The working mechanism of P2P lending platforms with their data tools has worked relatively well in lowering the transaction costs throughout the financing process.

However, the P2P lending market is diverse, both in terms of working mechanisms and market segments. A general classification of P2P lending based on market segments might distinguish between market categories such as P2P consumer, business and property lending. The role of each segment, in line with other forms of crowdfunding, is briefly discussed in section 2.4. The current section concentrates on the two basic working mechanisms of P2P lending. The general idea behind P2P lending is that of a group of investors investing in loans, but different ‘business models’ are apparent within P2P lending. These business models are generally classified into two broad categories, one of which is direct P2P lending platforms covering companies that directly connect investors with borrowers.

Figure 2.1 presents the working mechanism of this category of the lending company. Investors invest in a loan directly through the P2P platform, which is also the lending company or the so-called ‘loan originator’. The P2P platform, as a lending company, transfers funds from investors to borrowers. The borrower returns the loan and additional interest to the investor. The P2P platform deducts a fee as a lending company and transfers the rest back to the investor’s account. Investors in P2P platforms invest directly in loans to borrowers. In this regard, investors know more about borrowers’ financial situations, with the P2P platform undertaking its own credit checks of borrowers. The P2P platform, as a lending company, is also in charge of debt collection. The benefits of this mechanism are greater transparency and direct access by borrowers to the P2P lending platform. However, this mechanism limits the growth of P2P lending platforms and might not create enough investment opportunities for diversification. The two platforms analysed in this study, LendingClub (USA) and Bondora (Estonia), fall into this category of P2P lending platform.

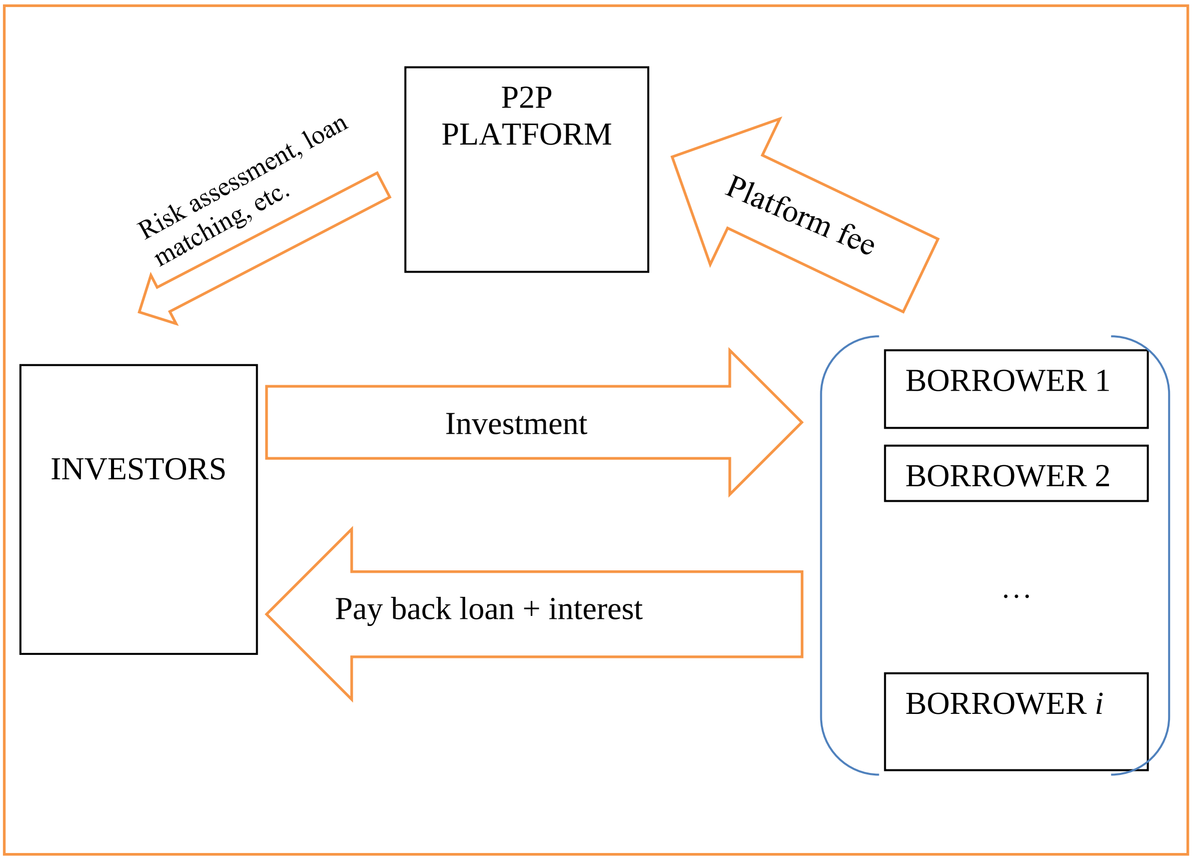

Figure 2.1: Working mechanism of P2P platform

Figure 2.2 illustrates the second category of P2P lending, the so-called P2P marketplace lenders. These companies do not issue their own loans via the P2P platform. Instead, they offer third-party loans on P2P marketplaces by simultaneously listing loans from multiple lending companies. These companies are called ‘loan originators’ and mostly consist of non-bank financial institutions. Under this mechanism, investors invest their money in a P2P marketplace which sends the money to the loan originator. The loan originator lends the money to the borrower and transfers the funds back to the P2P marketplace as the borrower repays the loan. Both the loan originator and the P2P marketplace deduct a fee before transferring the funds back to investors. Therefore, investors have more options for diversification via multiple loan originators. The P2P marketplace monitors the performance of its loan originators, with minimal information about borrowers provided to investors. The shortcomings of this mechanism are limited information about borrowers and heavy reliance on loan originators. Nevertheless, loan originators are mostly from the more regulated non-bank financial sectors and usually have safeguarding mechanisms, such as a buyback guarantee. Mintos (in Latvia), which is analysed in Chapter 6, falls into this P2P marketplace category.

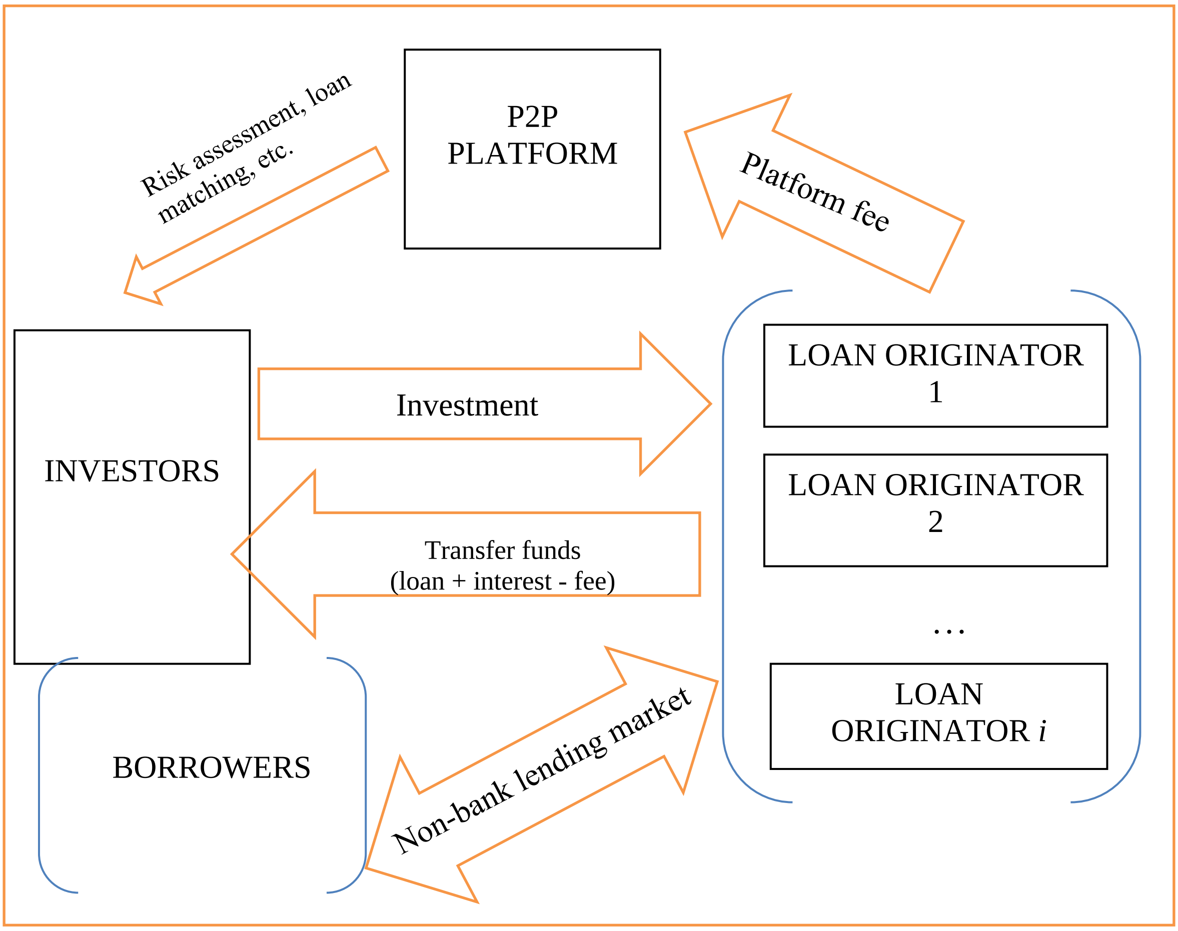

Figure 2.2: Working mechanism of P2P marketplace

2.4 Overview of P2P lending market trends

An overwhelming number of P2P lending platforms operate around the globe. Rau (2019) estimated that the total P2P lending volume around the world was US$208.4 billion in 2016. In the EU countries, 79 platforms successfully raised around €16.8 billion between 2010 and 2016 (ORCAMoney, 2017). Tomlinson et al. (2016) reported a cumulative annual growth rate of 87.4% for the European market and 109.4% for the UK market between 2010 and 2015. A report compiled by ReportLinker (2020) estimated a cumulative annual growth rate of 42.7% for the years 2020–2027.

If considered within the context of alternative financial markets, P2P lending grew to a new stabilised phase from 2016 onwards. Although exponential yearly growth of 152% occurred from 2010–2014, from 2014 onwards the rate of growth, although positive, has been a modest year on year (41% in 2016, 40% in 2017, 52% in 2018)

(Cambridge Centre for Alternative Finance [CCAF], 2020). In the EU, the volume of lending raised through crowdfunding platforms, on average, increased by 60% every year between 2013 and 2016 but the pace of expansion slowed after 2016 (Bank for International Settlements and Financial Stability Board [BIS], 2017). While recent growth rates are lower than in the early years of P2P lending, they remain significantly higher than those observed in most other industries. The UK remains the main contributor to the European P2P lending volumes, but this imbalance is decreasing as the volume in other European countries continues to rise. In 2016, the UK volume was 75% of the total European market (ORCAMoney, 2017). This market share, however, has continuously decreased since that point to 68% in 2017 and 57% in 2018.

Although the UK has remained a robust P2P lending market, the rest of Europe has been catching up. Several trends may be the cause, such as concerns over Brexit. The Baltic states of Estonia, Latvia and Lithuania started to emerge as contestants for leading the growth in the European P2P lending markets. These countries have created favourable business and regulatory environments and have an advanced information technology (IT) infrastructure, which allows firms to scale up relatively quickly and at considerably lower costs. These three countries combined produced a volume of US$539 million in P2P lending in 2018, making them the sixth-largest in Europe. This was due to a growth rate of 103% and was more than double their volume of US$265 million in 2017, which itself followed earlier growth of 72% from a volume of US$151 million in 2016. The US remains the leading alternative finance market in the North American region, as well as the second-largest global market following China. In 2018, the US market reached US$61.1 billion in overall volume, accounting for 96% of overall regional activity in North America. This represented a 43% annual growth rate, a significant year-on-year increase when compared to previous years. In 2016, the US market grew by 22% from US$28.6 billion to US$34.86 billion, and by 24% in 2017 to US$43.8 billion (CCAF, 2020).

Another important aspect of P2P lending is its dominant role in alternative finance. Table 2.1 presents the volumes of the respective alternative lending markets in Continental Europe, with P2P consumer lending remaining the top model in volume, raising US$2.889 billion in Europe (Continental Europe excluding the UK). This volume has seen continual substantial annual growth, having grown by 89% from 2017. In 2017, P2P consumer lending contributed US$1.5 billion to the total volume, while 2016 saw a volume of $US771 million. During 2018, P2P business lending raised US$996.8 million in loans, followed by P2P/marketplace property lending with a volume of US$144.7 million in loans.

Table 2.1: Total funding volumes of alternative finance by model in Continental Europe 2014–2018 (US$ millions)

	2018	2017	2016	2015	2014
P2P/Marketplace Consumer Lending	2889.4	1570.3	771.2	406.1	364.9
P2P/Marketplace Business Lending	996.8	526.2	387.5	235.4	123.7
P2P/Marketplace Property Lending	144.7	75.1	105.3	0	0
Invoice Trading	803	604.3	278.7	89.5	8.8
Real Estate Crowdfunding	600.1	291.8	121.1	29.9	0
Equity-based Crowdfunding	278.1	237.9	242	176.9	109.8
Reward-based Crowdfunding	175.4	179.1	211.1	154.6	159.9
Debt-based Securities	167.8	84.8	25.3	11.9	4.8
Donation-based Crowdfunding	62.4	107	65.4	2.6	0
Balance Sheet Property Lending	1378.4				
Balance Sheet Consumer Lending	99.8	3.4	18.5	0	0
Balance Sheet Business Lending	80.5	24.4	0	0	0
Minibonds	42.8	59.9	35.9	24.1	21.7
Revenue Sharing	3.5	1.8	9.3	0.6	0
Community Shares	1.6	0	0	0	0
Other	6.3	32.8	11.2	0	0

Sources: (CCAF, 2020; Zhang, Ziegler, Mammadova, Johanson, Gray, & Yerolemou, 2018)

Table 2.2 provides the volumes of respective alternative lending markets in the United States (USA). In 2018, the volume from the P2P/marketplace consumer lending model accounted for 41.5% of the US market, becoming the largest model for the year, and growing 73% from the 2017 level. The P2P/marketplace business lending model, conversely, accounted for US$2 billion in 2018, a 40% increase from the previous year, but only representing 3.3% of the US market. Similarly, in the consumer lending platforms, firms focused on financing businesses, with this tending to overlap considerably across the balance sheet and P2P/marketplace lending models. In this case, the emphasis of activity skewed towards the balance sheet model. P2P/marketplace property lending in the USA was relatively small, raising US$0.66 billion in 2018. This represents an annual decrease, accounting for a 47% drop from US$1.23 billion in 2017. However, one should note rapid spikes in the market resulting from the exit or entry of some firms. Moreover, given the close nature of the alternative finance sector, firms might operate with multiple forms of lending. Firms are also prone to shifting market sectors and changing their business models. Until the market reaches maturity, further refinement would be needed to more accurately interpret how firms are defining their own activity. Another trend of the market is the transformation of key firms into digital banking or other new models. This trend might explain low volumes and the growth of certain types of P2P lending practice, as well as certain types of alternative financing firm.

Table 2.2: Total funding volumes of alternative finance by model in the USA 2014–2018 (US$ billions)

	2018	2017	2016	2015	2014
P2P/Marketplace Consumer Lending	25.39	14.66	21.05	17.92	7.64
P2P/Marketplace Business Lending	2.03	1.45	1.33	2.58	0.98
Reward-based Crowdfunding	0.38	0.41	0.55	0.6	0.46
P2P/Marketplace Property Lending	0.66	1.23	1.04	0.78	0.13
Real Estate Crowdfunding	1.79	1.85	0.81	0.47	0.13
Donation-based Crowdfunding	0.31	0.18	0.22	0.14	0.15
Balance Sheet Property Lending	9.53	0.67			
Equity-based Crowdfunding	0.51	0.24	0.55	0.59	0.27
Revenue Sharing	0.25	0.01	0.02		
Balance Sheet Consumer Lending	7.52	15.2	2.94	3.07	0.69
Balance Sheet Business Lending	12.39	6.73	6	2.25	1.11
Invoice Trading	0.14	0.11			
Debt-based Securities	0.01	0	0.03		
Other	0.23	0.07			

Source: (CCAF, 2020; B. Zhang et al., 2018)

Despite its rapid early growth, P2P lending still represents a small fraction of total bank lending, with the growth rates having considerably slowed during the past few years. Even in the UK, where P2P lending is most rapidly developing, it accounts for 0.53% of total unsecured consumer lending and 0.45% of total small and medium-sized enterprise (SME) lending (Milne & Parboteeah, 2016). The impressive early growth of this market indicates a favourable business environment rather than the strength of P2P lending markets. Since the GFC and until the COVID-19 pandemic hit the global market, economic conditions were generally boosting the growth of the P2P lending industry.

External factors such as low-interest rates combined with stable economic growth ensured that the industry did not face serious challenges. Conversely, the expected global economic recession as the result of the global COVID-19 pandemic is the first to be experienced by the P2P lending industry. The future of the industry is still uncertain, as it largely depends on complex and interrelated macroeconomic factors (J. Li, Liao, Wang, & Xiang, 2016).

Early indications of the survival of the platforms under the default wave came in China during 2018 and 2019. During this time, the US$190 billion Chinese P2P lending market suffered considerably when investors rushed to withdraw their money (Wildau & Jia, 2018). Regulatory changes and the wave of defaults created problems of ‘failing platforms’ in China. As reported by Bloomberg (2018) and A. Liu (2019), the cumulative number of failed P2P lending platforms in the Chinese P2P lending market reached a staggering 4,334 platforms or 70% of active platforms. Tomlinson et al. (2016) admitted that the interest rate environment alone might lead to an expected divergence in the P2P lending penetration in the UK market from £0.5 billion (under a normalised interest rate environment) to £35.5 billion (under the current interest rate environment) by 2025. This raised concerns about the future of the P2P lending industry and cast doubt on the underlying reasons hidden behind the emergence of these platforms.

2.5 Role of regulation in P2P lending industry

In most countries, P2P lending comprises a negligible part of the financial market. Therefore, the governments of these countries have not considered introducing separate regulation for P2P lending (or other alternative lending practices) for them to be viable. However, in most countries where alternative lending has matured, governments have separate regulations for this industry. The UK, the USA, China and Australia have their separate regulatory bodies for alternative lending practices (including P2P lending). In the UK, for example, P2P lending is regulated by the Financial Conduct Authority (FCA). The UK government has even created a special innovative finance individual savings account (ISA) to help consumers invest in P2P lending platforms. Regulation in the UK related to P2P lending was under revision, with the underlying macroeconomic changes having a considerable impact on the loan portfolio of lending platforms. Generally, in the UK and the USA, P2P lending regulations are not tough. Although the P2P platforms are not considered to be banks which relieves them from a range of regulatory hurdles, they are still required to go through certain registration and licensing processes.

The continental P2P lending market in Europe is growing, partially due to revisions to existing regulatory frameworks, but also in anticipation of the European Crowdfunding Service Provider Regime, which will create a harmonised legal framework across the continent for cross-border crowdfunding. The Baltic states of Estonia, Latvia and Lithuania have created favourable business and regulatory environments and have an advanced IT infrastructure which allows firms to scale up relatively quickly and at considerably lower costs. In China, regulation for P2P lending was non-existent until 2015. However, from July 2015, the Chinese government introduced certain levels of regulation bringing capital requirements, loan guarantees and a national registry into P2P lending platforms (Deer, Mi, & Yu, 2016). Australia was a late adopter of regulations for alternative lending and was generally behind its peers in the region (China and New Zealand, for instance). The Australian Securities and Investment Commission (ASIC) currently has certain licensing and disclosure requirements for alternative lending practices.

Only a handful of countries, such as the UK and the USA, have developed regulatory frameworks that could address industry problems at times of distress (Warren, 2016). However, the assessment of regulations in the USA and the UK undertaken by Warren (2016) highlighted that the fragmented US system was the least promising. It was found that regulation in the USA could potentially fail to comprehensively respond to risks posed by P2P lending markets. The UK regulations, in contrast, were concluded to be a promising example. Regulations in the UK are concentrated on the sole regulator undertaking a practical attitude to regulation. Verstein (2011) also highlighted that regulation implemented by the US Securities and Exchange Commission (SEC) essentially misjudged the original and innovative nature of P2P lending and endangered the survival of its marketplaces. Table 2.3 presents the diversity in regulations and different approaches implemented in the regulatory environments of some countries selected for the current study.

Table 2.3: Peer-to-peer (P2P) lending market regulatory overview

Regulatory Aspects	USA	UK	China	Australia	New Zealand	Germany
Rule based vs Principle based	Rule	Principle	Both	Rule	Rule	Rule
Securitisation	Yes	No	Yes (with restrictions)	No	No	No
Deposit insurance	Yes	No	Yes	No	No	No
Disclosure to investors	Yes	Yes	Yes	Yes	No	Yes
Disclosure to borrowers	Yes	Yes	Yes	Yes	Yes	Yes
Registration requirement	Depends on state	Yes	Yes	Yes	Yes	Yes

Sources: (CCAF, 2020; Cumming, 2020; Ziegler et al., 2017)

2.6 Considerations related to social welfare

As in other fields of economics and finance, the success of business entities is not only measured by their profitability and riskiness, but also by their impact on social welfare. In this regard, considerations related to social welfare can be traced back to asymmetric information. Early theoretical models by Stiglitz and Weiss (1981, 1992) and Bester (1985) highlighted that imperfect information in financial markets can lead to excess supply and/or demand creating a departure from Walrasian equilibria. As markets expand by offering more and more alternative sources of funds, adverse selection and a departure from equilibrium are inevitable (Bester, 1985). Understanding the impact of this departure on both sides of the market – the P2P platform and social welfare – is vital to the same extent as is the establishment of the relationship between loan volumes and quality.

Several studies, such as those by Beck (2013), Beck, Levine and Loayza (2000), Ryan (2011) and Fungáčová, Shamshur and Weill (2017), analysed the impact of traditional financial institutions on social welfare. Berger and Gleisner (2009) and Schaeck, Čihák and Wolfe (2009) used cost of capital as a proxy for measuring social welfare in the banking sector and postulated that increased lending leads to a decrease in social welfare. One of the early studies by Chan (1983) investigated venture capital investments and compared an economy with screening agents (venture capitalists) with one without them, indicating that introducing such agents enhanced welfare. Later studies of alternative financial markets, such as microfinance (which is closer to P2P lending markets), analysed the social failure of financial institutions using both a case study approach and regression analysis (Dorfleitner, Leidl, & Priberny, 2014; Dorfleitner, Priberny, & Röhe, 2017; Rozas, 2011). Various indicators were used to measure social failures such as governance and outreach indicators (Mersland & Strøm, 2009) or a dummy variable indicating social failure (Dorfleitner et al., 2017).

Prior studies have not comprehensively examined the impact of P2P lending volumes on social welfare. Wei and Lin (2016), using more than 13,000 loans from the Prosper.com platform, examined the social welfare effects (in line with interest rate determination, probability of funding and probability of default) of market mechanisms on P2P lending markets, and showed the link between social welfare, platform profits and borrower surplus. Wei and Lin (2016) formally developed a model showing that under the auction pricing mechanism[4], social welfare can be higher than under the posted pricing mechanism[5] in the P2P lending market. Nevertheless, Wei and Lin (2016) limited their scope to a single platform (Prosper.com based in the USA). The current study considers the interaction between the interest rate and probability of default in the context of loan volumes. In this regard, it expands on the findings of the existing literature by exploring the impact of high loan volumes on social welfare costs for borrowers (as represented in higher interest rates).

2.7 Conclusion

In their modern form, P2P lending practices have not been around for a lengthy period of time. Empirical evidence is strongly consistent with the view that P2P lending spurs on entrepreneurial activity. This chapter first introduced the basic definitions of P2P lending and some of the main indicators of P2P lending volumes in selected countries and regions. It explained how some P2P platforms work with regard to carrying out due diligence on entrepreneurial firms, providing ratings on entrepreneurial firms and information disclosure. Since the GFC, P2P lending has grown extensively. This chapter reviewed the

[4] Under the auction pricing mechanism, borrowers set a reservation or maximum interest rate that they are willing to accept.

[5] Under the posted pricing mechanism, the platform pre-sets interest rates for the loan based on the borrower's creditworthiness.

evidence that P2P lending platforms operate within the entrepreneurial ecosystem and generally work as a complement to, and not as a substitute for, traditional banks. This chapter also explained the typical mechanisms of P2P lending practices and their regulatory and social welfare aspects. Unlike most earlier studies, the study moved beyond a descriptive analysis of the industry. This study instead sought further evidence on the determinants of loan default in P2P lending via extensive empirical analyses. With such further evidence emerging from an empirical analysis, in the long run, improved performance of P2P lending would guide investors on the best practices of this industry, thus enabling successful investing and borrowing.

Chapter 3:

Literature Review

3.1 Introduction

This literature review is intended to highlight the role of crowdfunding and P2P lending practices in terms of their effects on current developments in the financial sector. The review plays a significant role in providing evidence-based information for financial lending platforms, and chiefly for P2P lending models. This chapter presents important accounts of the literature on P2P lending in line with related studies in traditional and alternative finance.

The study used Google Scholar, ScienceDirect and USQ Library Search services to search for studies in the literature. The search to locate studies for the literature review was optimised by using the following keywords: “digital finance”, “crowdfunding”, “peer-to-peer lending”, “COVID-19 pandemic”, “alternative finance”, “Fintech” and “determinants of P2P lending”. Search findings were then filtered based on peer-reviewed journals or reports by established research schools and institutions. Other types of research studies, such as working papers and unpublished works, were included if their findings were supported by peer-reviewed studies. Searches using the following keywords: “performance evaluation of P2P lending”, “credit risk in P2P lending”, “liquidity risk in P2P lending” and “cross-country study of P2P lending” did not yield viable results. In fact, prominent studies (Dushnitsky, Guerini, Piva, & Rossi-Lamastra, 2016; Wei & Lin, 2016; Li, Liao, Wang, & Xiang, 2020) have highlighted these aspects (performance evaluation, credit and liquidity risk) of P2P lending practices as prospective avenues for future research studies.

Search results based on the above-identified keywords and filtering criteria led to an outcome yielding a very limited number of studies. Search results also included studies on crowdfunding as P2P lending is regarded as part of crowdfunding.[6] The limited availability of relevant literature has prevented the current study from raising comprehensive debates and issues related to the research topic. Instead, this study

[6] Refer to Chapter 2 for the description of P2P lending as part of crowdfunding.

establishes the value of the research and the nature of its contribution based on the challenges faced by investors, as highlighted in Assenova et al. (2016) and Cumming (2020). Thus, this chapter discusses originating studies that describe the P2P lending market and explores its determinants, whereas the main hypotheses of this study are developed based on traditional financial literature. This strategy has been followed in most of the related literature, such as Dushnitsky et al. (2016) and Wei and Lin (2016).

Section 3.2 describes the literature related to the origins and rationale behind the existence of the P2P lending market. Section 3.3 explains the impact of location factors on the development of the P2P lending market. Section 3.3's discussion of the literature emphasises the cross-country and regional characteristics, as included in the empirical analyses in Chapters 5, 6 and 7. Section 3.4 discusses the determinants of P2P lending, emphasising the rationale behind the inclusion of borrower-specific and demographic factors included in the empirical analyses. Section 3.5 formulates the hypotheses to be tested in the empirical chapters. Section 3.6 explores the limited literature related to the impact of pandemics on the financial sector and the economy overall. Section 3.7 concludes this chapter.

3.2 Extent of studies on crowdfunding and P2P lending

During the past decade, crowdfunding and P2P lending models have achieved significant success. These forms of lending have emerged as a sustainable process for funding new start-ups. Nevertheless, research studies on this issue have been limited, with only a small number of published peer-reviewed papers. Moreover, the studies have been largely descriptive by nature, offering only a limited degree of analytical consideration. One of the early studies on this topic by Schwienbacher and Larralde (2010) proposed one of the initial definitions and understandings of crowdfunding. The paper considered and briefly analysed a case study of a French music crowdfunding start-up. Subsequently, several attempts were made to build a theoretical model to explain and highlight the reasons why individuals would participate in crowdfunding (Belleflamme, Lambert, & Schwienbacher, 2014).

Existing studies also highlight crowdfunding and P2P lending platforms as tools that incorporate all means of investment but with some extra advantages. (Schwienbacher & Larralde, 2010) and Mollick (2014) postulated the role played by crowdfunding and

P2P platforms in allowing the testing of marketing campaigns and the launch of new products. Segal (2015) postulated that P2P lending may be a viable financing alternative for small businesses, particularly given the post-recession credit market.

The P2P platforms are considered to be inspired by social networking that allows active customer participation in sharing information via online communities. This active participation allows customers to provide suggestions on new proposals and brands (Ordanini & Parasuraman, 2012). At the same time, the platforms can be used as the means to demonstrate demand for a proposed product, with successful initiatives becoming a signal to venture capitalists of a potential good long-term investment, possibly leading to additional future financing for crowdfunders (Mollick, 2014). Agrawal, Catalini and Goldfarb (2013), in turn, interpreted the expansion of crowdfunding and P2P lending in economic terms via transaction costs, reputation and market design.

Another study by Van Wingerden and Ryan (2011) highlighted the difference between intrinsic motivations ("control of the use of innovation", "improvement of current circumstances", "enjoyment", "sense of involvement") and extrinsic motivations ("financial reward"). Studies by Shang and Croson, (2009), Kuppuswamy and Bayus (2013) and Burtch, Ghose and Wattal (2013) concentrated on the issue of investment incentives over time. These papers investigated the positive treatment of projects with previous pledges and distinguished between reputable and new funders.

Peer-to-peer (P2P) lending platforms also allow lenders and borrowers to share information via online communities, with this inspired by social networking to a certain extent. Several prior papers analysed the motives behind the use of crowdfunding and P2P platforms to raise funds. Belleflamme, Omrani, and Peitz (2015) stated that the main motives behind the launch of crowdfunding initiatives are raising money, getting public attention and obtaining feedback on products and services. Gerber and Hui (2013) indicated the importance of obtaining funds and retaining complete control over the project at the same time. Their study also highlighted the process of validation, connecting with others and reproducing successful earlier practices as reasons for becoming involved in crowdfunding.

From the investors' perspective, Harms (2007) postulated self-expression and enjoyment as the main motivations behind crowdfunding investments. The study was based on responses to questionnaires distributed to 196 investors. Investors indicated that they also contributed to crowdfunding projects due to the economic value and positive tangible output of these projects. However, "personal utility" was prevalent as a specific aspect for motivation among investors to become involved in crowdfunding and P2P lending. In this regard, the specific purpose of the individual consumer tends to outweigh the practical benefits of the projects in which he/she has invested (Harms, 2007).

Shang and Croson (2009) and Burtch et al. (2013) investigated how investment incentives change over time. Their studies compared new and reputable funders and found that the projects with previous pledges were treated as relatively positive. Mollick's (2014) study considered the success factors of crowdfunding projects. It used a database consisting of posted projects on Kickstarter and, due to its context, was largely exploratory. It generally considered the success factors of crowdfunding projects. The current study proposes to concentrate on equity- or debt-based crowdfunding, the funding environment and the importance of communities.

3.3 Crowdfunding and P2P lending across different locations and countries

In terms of the location of investments, existing studies have proposed that firms in their early stages of development largely rely on local investors, owing to the low costs of information gathering, monitoring progress and providing input (Zook, 2002; Mason, 2007). However, online platforms tend to contradict this proposition as they decrease most of the highlighted costs (Agrawal, Catalini, & Goldfarb, 2010). To be specific, platforms that operate online over the internet are inclined to challenge this proposal, as the use of an online marketplace, accessible from everywhere, reduces most of the indicated costs (Agrawal et al., 2010). For example, the mean distance between venture capital and the target firm is found to be 70 miles (approx. 112 kilometres [km]), while it is 3,000 miles (approx. 4,830 km) for online lending platforms (Stuart & Sorenson, 2005). Nevertheless, prior studies find geography to be an important component in the context of the P2P lending market (Mollick, 2014). The studies in the literature, which are mostly based on exploratory analysis, have continued to indicate the importance of geography and the location of investments in online crowdfunding and P2P lending frameworks

(Mollick, 2014). The study by Senney (2016) indicated that local lenders undertake the bidding earlier and are more informed in the sense that they are better able to evaluate the underlying risk of borrowers. Atz and Bholat (2016) compared P2P lending patterns in different regions of the UK and found no significant difference in interest rates, loan volume and terms between the regions under consideration.

Most existing studies have highlighted the importance of crowdfunding and P2P lending in eliminating boundaries related to the location. However, few studies have concentrated on regional differences in P2P lending's funding patterns. A few existing studies (Verstein, 2011, Hu & Yang, 2014, Shi & Guan, 2016; Warren, 2016) have considered regional, or cross-country differences, but these studies are mostly descriptive. The only known empirical cross-country study was conducted by Dushnitsky et al. (2016). This study considered the crowdfunding industry in Europe by using a database comprising the number of crowdfunding platforms across Europe between 2008 and 2014. The study postulated that country-specific factors, such as economic, legal and sociological factors, are important for the development of the industry. Dushnitsky et al. (2016), in their paper, indicated that future studies may benefit by considering the amount of capital and the economic performance of platforms and by extending the time-scale of the data set. Mollick (2014) proposed that studies should concentrate on equity- or debt-based crowdfunding (P2P lending), the funding environment and the importance of communities. Accordingly, the research questions of the current study are concentrated on the above-mentioned shortcomings and gaps highlighted in prior studies.

3.4 Determinants of P2P lending

In identifying the determinants of P2P lending, one central issue is the determining factors that affect lenders' bidding strategies and the loan funding success rate. An increasing amount of studies has sought to verify the determinants that affect lenders' strategies for bidding and borrowers' loan funding success rate. In this regard, the prior literature analysed factors such as user credit information, loan characteristics, demographic information and soft information (Feng, Fan, & Yoon, 2015). Puro, Teich, Wallenius and Wallenius (2010), Freedman and Jin (2008), Lin et al. (2013) and Bodie, Kane and Marcus (2012) highlighted factors such as interest rate and size and maturity of loans as having a significant impact on the probability of funding success. Iyer, Khwaja, Luttmer and Shue (2009), Freedman and Jin (2008) and Yum, Lee and Chae (2012) indicated that borrowing history and credit rating mainly determine the probability of successful funding. Another study concentrated on demographics in the lending process, indicating that women seem to tolerate a lower interest rate from both the borrowing and lending sides; younger borrowers are, in general, more successful; and a racial disadvantage is present in both funding success rate and interest rate paid (Feng et al., 2015).

Wei and Lin's (2016) study examined interest rate determination, probability of funding and probability of default in P2P lending. The study analysed the case of Prosper.com with the data set containing the listing of more than 13,000 loans. Their study first developed models of market mechanisms for the auction and posted prices bidding processes. Wei and Lin (2016) empirically tested the impact of these two mechanisms on interest rate and borrower defaults. They indicated that linking market mechanisms to inter-platform competition should be considered as a promising area for future research. By considering multiple platforms, the current study materialises work on areas considered to be prospective in prior studies, such as that by Wei and Lin (2016).

Several studies also considered the determinants of loan default among P2P lenders. In this regard, the study of Serrano-Cinca, Gutiérrez-Nieto and López-Palacios (2015) applied logistic regression with loan data collected from LendingClub (USA). Their study highlighted the importance of grades assigned by the P2P lending site in predicting loan defaults. According to the study, these grades were essential for forecasting loan defaults. Another study conducted by Emekter, et al. (2015) highlighted that credit score, debt-to-income (DTI) ratio, Fair Isaac Corporation (FICO) score and revolving line utilisation play an important role in loan defaults. Herzenstein, Andrews, Dholakia and Lyandres (2011) and Lee and Lee (2012) concentrated on 'herding behaviour' in which the behaviour of a few investors is followed by others. These two studies empirically documented that lenders have a greater likelihood of bidding on an auction with more bids ('strategic herding behaviour'). Lin and Viswanathan (2014) and Duarte, Siegel and Young (2012) highlighted the importance of so-called 'home bias' and 'trust'. These two factors were found to significantly affect loan default probabilities among crowdfunding and P2P lending platforms. Greiner and Wang (2010) and Freedman and Jin (2014) proposed the social network effect as a significant factor for explaining default probabilities among P2P lenders. Social networks are a specific aspect of online lending practices where investors place much weight on factors, such as the number of friends on online networking platforms.

Several studies considered the lending behaviour of P2P lenders in China. Chen and Wu (2014), while surveying P2P lending platforms in China, indicated that 'trust' is the most important factor affecting the lender's willingness to lend. Chen and Han (2012) conducted a comparative study of P2P lending between China and the USA, relying on so-called 'hard' and 'soft' credit information. In this respect, the study found that lenders in China rely more on 'soft' information compared to their US counterparts. J. Li and Zhu (2013), in applying OLS regression, identified factors such as credit rating, borrowing history and amount of listed loans as determinants of the interest rates of successful loans. Zhang, Yang and Pan (2015) also relied on OLS regression and indicated that the bidding record has a greater influence on online Chinese P2P lending, compared to other factors, and that Chinese users rely heavily on social capital. The studies of Song and Han (2013) and Wen and Wu (2014) explored the determinants of both the loan success rate and interest rate among P2P lenders. These studies were based on logit and OLS regressions and confirmed the importance of credit rating and borrowing history as main factors defining the success rate and interest rate of P2P loans. Jiang, Liao, Wang and Zhang (2019) examined more than 5,000 P2P lenders established in China, finding that platforms backed by state-owned enterprises had larger facilitated loan amounts, attracted more lenders and paid lower interest rates to lenders. Li, Liao, Wang, & Xiang (2020) explored the weekly trading data from P2P lending platforms in China and indicated that venture capital-backed platforms were less likely to default than non-venture capital-backed platforms. Based on the above discussion, existing studies confirmed that no significant difference was found between Chinese P2P lenders and their Western peers.

Although P2P lending has been growing rapidly around the world, studies in the literature indicate a lack of empirical investigation of this market. Specifically, no countrywide research with a complete data set has been undertaken that may be able to indicate regional differences within a country. At the same time, no research has specifically highlighted the importance of macroeconomic indicators by including these indicators in regression models. Although the theoretical perspective is available to support the impact of macroeconomic variables on financial market performance, hardly any research has specifically highlighted the impact of macroeconomic factors by including these variables in the empirical analysis of the risk factors of P2P lending. Most studies in the existing literature, as highlighted in this section, have solely concentrated on borrower-specific determinants. Existing studies have generally ignored the country-specific and platform-specific aspects of the P2P lending industry (Li et al., 2020; Liu, Shang, Wu, & Chen, 2020; Serrano-Cinca et al., 2015). The literature has also highlighted the need for further evidence on the determinants of loan defaults in P2P lending across platforms and borrowers (Cumming, 2020).

Therefore, as the practices of crowdfunding and P2P lending are being developed with their complementary policies, an urgent need has emerged for empirical investigations of this topic, with appropriate reference to existing theoretical understandings. Based on these shortcomings in the existing literature, the current study concentrates on the specific determinants of P2P lending with particular emphasis on macroeconomic factors. Chapters 5 and 6 concentrate on specific macroeconomic determinants (namely, interest rate and inflation) of P2P lending, as specified in the hypotheses in section 3.5 below.

3.5 Formulation of the study's hypotheses

The main empirical analysis of this study concentrates on estimating the predictive relationship between interest rate/inflation and loan defaults (delinquencies) among borrowers of P2P lending platforms. The review of the existing literature indicated that insufficient theoretical and empirical literature is available for building the full methodological foundations of this study. Prior studies, such as those by Hu and Yang (2014) and Shi and Guan (2016), have not used an empirical modelling framework nor have they undertaken extensive cross-country analysis. The only known study, namely, the work of Dushnitsky et al. (2016), is limited to considering the number of existing crowdfunding platforms as the dependent variable with no theoretical grounding. The same study has acknowledged this limitation, identifying the economic performance of P2P platforms as an area for future research.

This study draws its research hypotheses based on the underlying existence of credit risk among P2P lending platforms. Lenders to P2P lending platforms have a high credit risk in the case of borrower defaults as borrowers have only one or a few counterparties. Credit risk stems from the possibility of the borrower defaulting on principal or interest payments, due to his/her inability or lack of willingness to repay them. With this regarded as a risky investment, P2P lenders ask for a premium over the risk-free interest rate. The value of the credit spread over the risk-free interest rate is linked to credit quality which is defined as the estimated default probability and the estimated loss in the event of default (Bhaduri, 1977). Following the literature on traditional finance (Louzis, Vouldis, & Metaxas, 2012; Ghosh, 2015), the current study follows a broader definition of financial distress among borrowers. This study combines default loans with delinquent loans ('bad loans') that better characterise financial distress than default loans.

Accordingly, interest rates should be more a matter of credit risk than a matter of cost. The first research question is:

> does an increase in interest rates lead to more defaults (delinquencies) among P2P borrowers?

The prevalent belief among policymakers – and basic economic theory – would seem to suggest that it should. The real value of borrowers' debt tends to increase as real lending rates rise. Consequently, this makes debt servicing more expensive (Blanchard, 2019; Luzzetti & Neumuller, 2016).

Empirical evidence from traditional financial markets is mixed in this regard, with a hike in interest rate normally limiting the ability of borrowers to meet their debt obligation. Thus, a surge in interest rate increases loan defaults and, hence, non-performing loans (NPLs) (Beck, 2013; Espinoza & Prasad, 2010; Louzis et al., 2012). Moreover, greater interest rate uncertainty affects banks' sources of funds, in turn, influencing the growth in loans and, hence, in non-performing loans (NPLs) (Brewer, Deshmukh, & Opiela, 2014; Louzis et al., 2012; Messai & Jouini, 2013). However, Goel and Hasan (2011), Jakubík (2006) and Virolainen (2004) produced different findings in economies where higher default rates were observed with lower interest rates. The study by Ghosh (2015) indicated a largely insignificant relationship between the real interest rate and NPLs among US financial institutions.

Studies among P2P lending platforms are extremely limited in number with, to the best of the author's knowledge, no research specifically examining this issue. Therefore, the first hypothesis explored in this study is as follows:

> Hypothesis 1: An increase in interest rates causes an increase in defaults (delinquencies) in P2P lending markets.

The second research question for this study is:

> Does an increase in inflation lead to more defaults (delinquencies) among P2P borrowers?

The role of the inflation rate in determining financial lending and consequent defaults has been prevalent in the financial literature. From the theoretical perspective, inflation is often caused by a lower interest rate, and it devalues the real value of debt, stimulating more household spending and even reducing unemployment (the Phillips curve), thus producing a negative sign. On the other hand, inflation erodes the real income value (as wages do not rise as inflation rises), making debt repayment more difficult as the available funds are less, with this ultimately deteriorating the quality of the loan portfolio.

Empirical evidence appears to be mixed among traditional financial markets with ambiguous relationships observed between inflation and non-performing loans (NPLs) (Nkusu, 2011; Skarica, 2014). High inflation periods, for example, are found to be periods in which distortions occur in lending, borrowing and saving decisions (Chopin & Zhong, 2001). This may, therefore lead to reduced borrowing in financial markets or from financial institutions (Apergis & Eleftheriou, 2002; Boyd et al., 2001; Wongbangpo & Sharma, 2002). On the other hand, some studies have indicated the positive impact of inflation on NPLs for commercial banks (Ghosh, 2015; Klein, 2013).

With no prior studies having analysed the inflation rate as a determinant of alternative sources of funding in an economy such as the P2P lending market, the next hypothesis is as follows:

> Hypothesis 2: An increase in inflation rates causes an increase in loan defaults (delinquencies) in P2P lending markets.

This study tests Hypotheses 1 and 2 in the empirical chapters, firstly, in the context of the USA (state-wise in Chapter 5) and then in Continental Europe (country-wise in Chapter 6) using a platform loan book data set (in Chapters 5 and 6).

3.6 Pandemics and the financial sector

Peer-to-peer (P2P) lending gained its comparative advantage by diversifying across a large number of borrowers, thus substantially providing protection against the variability of defaults (Cumming & Hornuf, 2018). What remains unprotected are the loan loss and default risk over the business cycle. Losses are expected to increase substantially with a major economic downturn which could easily exhaust investor funds (Bolt et al., 2012). The current economic downturn resulting from the COVID-19 pandemic has increased the likelihood of unsustainable losses by the industry. At the time of writing this thesis, the COVID-19 pandemic had significantly impacted the global economy. In fact, the expected global economic downturn is the first to be experienced by this industry. As the COVID-19 pandemic is affecting financial markets, the dynamics of successful P2P lending need to be better understood under the conditions of financial distress. This section reviews some of the literature on the impact of this pandemic on the financial sector and the economy. The studies are in their infancy with no studies yet conducted on P2P or alternative lending markets.

Pandemics are historically known to have a large associated economic cost that can significantly influence financial systems (Haacker, 2004; Santaeulalia-Llopis, 2008; Yach, Stuckler, & Brownell, 2006). The outbreak of the COVID-19 virus at a global level has resulted in a worldwide pandemic with national responses instigating substantial constraints on various economic activities. According to Agosto and Giudici (2020), the digital form of financing based on online and social networking is anticipated to be largely affected by the catastrophic outbreak of this highly contagious disease. Their study performed contagion monitoring to establish the impact of COVID-19 on digital finance. With the help of an application of statistical models, the short-term and long-term impact on economic changes were analysed with changes in infection cases in China, the first country of the world affected by COVID-19. Agosto and Giudici (2020) highlighted that, in the first week of February 2020 as cases of COVID-19 accelerated, the contagion spread the virus, and the Shanghai Stock Exchange (SSE) composite index plummeted. In the later stages of the pandemic, the negative correlation between SSE returns and reported COVID-19 cases, although weaker, is being observed.

Goodell (2020) emphasised the lack of studies related to the impact of the COVID-19 pandemic on the financial sector, but this can be paralleled to other survivable disasters, inclusive of earthquakes, volcanic eruptions, air disasters and terrorist attacks. In the earlier revealed disasters, the effect of these events is generally restricted, which is in contrast with COVID-19, which has an undesirable impact at the global level. Goodell (2020) also stated that, in the case of not-survivable catastrophes, economic markets will not be influenced as they seem to be 'beside the point' in that situation. However, with catastrophes like COVID-19 that are considered survivable, the impact on financial markets is affected and therefore relevant. COVID-19, as a survivable global pandemic, is projected to have a long-term impression on organisational financing and the cost of capital (Goodell, 2020). Elnahas, Kim and Kim (2018) argued that organisations located in a disaster-prone area have a tendency to be less leveraged. For that reason, COVID-19 is estimated to bring together less leveraged principal structures. As a result, the COVID-19 pandemic is causing a destructive direct global economic impact that is present in every area of the globe.

Bloom and Cadarette (2019) debated the numerous concerns of the pandemic, such as the impact on the health care system, loss of occupation and loss of activities related to the economy, holiday businesses and foreign funding. The influence of a pandemic on the economy at the global level has been undervalued and, as a result, financial prudence has tended to underinvest in preparation for such a situation (Fan, Jamison, & Summers, 2018). This became more prominent when spending behaviours changed globally after the outbreak of the COVID-19 pandemic. This resulted in a downtrend in expenditure and home-based demand (Haacker, 2004). This is in accordance with the study of Leoni (2013) which related to the spread of human immunodeficiency virus (HIV) and its affirmative association with deposit withdrawals in developing countries. In addition, Lagoarde-Segot and Leoni (2013) predicted that an enormous pandemic could result in the downfall of the banking industry. The advancing of loans to the poor would also be affected by the pandemic as investing groups and banks would be overstretched by the economic recession (Skoufias, 2003). Based on earlier studies related to previous pandemics, the COVID-19 pandemic is expected to influence the economic sector in a similar manner with withdrawal spikes and a disproportionate reduction in loans to the poor.

Nevertheless, small businesses and low-income households can benefit from digital financing and online banking services. Several support programs for financing have been formulated by government bodies to ease the financial problems of lending and fundraising for small enterprises during this catastrophic outbreak of COVID-19. These secure financial programs are intended to mitigate the downturn of the economy and fill the gaps in order to maintain and survive the economic challenges being faced, and yet to be faced, by countries in response to the pandemic crisis (Civelek & Xiarewana, 2020).

Accordingly, it is expected that COVID-19 will have a significant effect on alternative lending markets, such as crowdfunding and P2P lending. Specifically, this study expects the current pandemic to negatively affect the liquidity of P2P lending platforms by creating a ‘bank-run’ type scenario (Peckham, 2013). Following typical behaviour in traditional financial markets, the pandemic triggered ‘herding behaviour’ among P2P lending market investors who rushed *en masse* to turn their stakes into cash. It is therefore hypothesised in this study that the World Health Organization (WHO)’s announcement of COVID-19 as a pandemic and the subsequent increase in cases increased the number of listings in Bondora’s Secondary Market.[7] This study also predicts that developments related to the pandemic reduced the probability of successfully ‘cashing-out’ investor holdings in loans through Bondora’s P2P lending. To this end, the additional hypotheses, the testing of which is described in Chapter 7, are based around the following general hypothesis[8]:

COVID-19 pandemic and secondary market listings:

Hypothesis 3: The COVID-19 pandemic significantly increased/reduced the daily number of listings/probability of success in Bondora’s Secondary Market.

[7] The Bondora P2P lending platform is further explained in Chapter 7.
[8] Hypothesis 3 is further developed in Chapter 7.

3.7 Conclusion

This review of the literature has established the background of the study based on previously published peer-reviewed articles related to crowdfunding and P2P lending. The literature has been extensively searched and analysed by gathering studies relevant to P2P lending. As a limited number of studies forms the literature related to the topic, this chapter explored general developments in the literature related to the P2P lending industry. In this regard, this chapter places emphasis on explanations of the definitions of P2P lending and its differences from the traditional financial market. The review highlighted the extent of the studies previously conducted on the techniques of fundraising, predominantly crowdfunding and P2P lending. The literature highlighted the importance and critical aspects of these lending platforms in terms of the feasibility of new ventures and well-reputed business programs. The studies provided evidence advocating the importance of the role played by these lending platforms in the development and marketing of new products, marketing strategies and campaigns related to these products. The usability of crowdfunding and P2P lending is further enhanced in terms of analysing the demand for a product. They can be used to establish long-term funding programs with investors and to evaluate the risks associated with fundraisers. The global aspects of crowdfunding and P2P lending platforms are also discussed in-depth, based on evidence from the limited existing studies, including factors related to regional and countrywide characteristics. The determinants affecting the lending of funds to new ventures or reputed organisations are discussed including lenders' strategies of bidding, the success rate of loan funding, characteristics of the loan, user credit information, demographics, 'hard'/'soft' information, interest rate, maturity of lending, loan amount, racial disadvantage, default/non-payment, credit score, debt-to-income (DTI) ratio, Fair Isaac Corporation (FICO) score, revolving line utilisation, herding behaviour and borrowing history, along with social capital. Most of these factors are based on the conceptual framework developed in section 1.6 and specifically highlighted in Figure 1.2. Together the review of the literature and the conceptual framework form the rationale behind the group of explanatory and independent control variables in the regression analyses reported in Chapters 5, 6 and 7.

In terms of the background of the main research questions and hypotheses, the literature review concentrated on comparative studies in traditional and alternative finance. Thus, the rate of interest and inflation in line with macroeconomic and country-specific variables used in the empirical chapters are based on equivalent theoretical and empirical studies. This strategy of hypotheses building has been followed in the related literature (Dushnitsky et al., 2016; Wei & Lin, 2016). This approach has built the foundations of the current study in terms of applying theoretical models from traditional finance to the P2P lending industry.

The last section of the literature review discussed publications related to the implications of the COVID-19 pandemic for the financial sector and economic situation in different countries. It explored how the behaviour of investors and borrowers changes as a result of global disasters such as pandemics. Section 3.6 also explored the impact of pandemics on decision-making processes for financial lending to consumers and organisations. The approach of relying on studies from prior pandemics was highlighted in Agosto and Giudici (2020). The respective hypotheses with regard to the COVID-19 pandemic are further developed in Chapter 7.

Chapter 4:

Data and Methodology

4.1 Outline of the chapter

This chapter elaborates in detail the process of analysis for this study. Accordingly, this chapter presents the philosophy of research methods and research strategies adopted. This chapter covers important issues such as preparation of the research, methods and procedure of aggregation of data, as well as the sampling decision. It explains how theoretical and empirical studies were used to draw the model and highlights the specific features of this model. Specifically, the technical aspects of the thesis are explained and elaborated. Through exploring existing literature, this study gained information about incurred credit risk while investing in P2P lending market. Thus, the explicit factors such as inflation and interest rate have been recognised to be important for this study. These important factors of credit risk then used for finding a relationship among these factors and the probability of default. This chapter also explains the data used for the model and its features.

4.2 Research philosophy and approach

The research methodology is to identify the fundamental approach for the study that will direct it into the correct path of exploration. Philosophies and approaches are the first and second layers of the 'research onion' respectively (Saunders, Lewis, & Thornhill, 2009). This study developed a certain conceptual framework based on the review of existing theoretical and empirical literature. This conceptual framework is then to be used to observe the tendencies in data analysis and insights may be drawn on the behaviour of a particular group of people (e.g. moral hazard with regard to borrowers). Accordingly, reflected from epistemological, ontological and axiological considerations (Saunders, Lewis, Thornhill, & Bristow, 2019) realism is set to be the research philosophy and uses a mix of quantitative and qualitative methods. Accordingly, this research uses several of the existing studies and is explanatory by nature. Additionally, it aims to create recommendations that are suggested to be further investigated by the players in P2P lending industry.

4.3 Research strategy

A number of different research strategies are available, e.g. experimental design that involves using a true experiment to guide non-experimental research (Bryman & Bell, 2011). This way of designing research may involve laboratory or field experiments. This study, however, uses a case study design that involves the analysis of a single industry in several countries. Case studies are very popular and widely used in business studies. Moreover, this strategy allows for combining several methods that are considered its main advantages (Bryman & Bell, 2011). To accomplish the research objectives and to address the research questions, this thesis draws on secondary data collection and relies on the database compiled by the author from different sources.

The research strategy is based on several countries (USA and EU member countries) and incorporates a database as one of its empirical data gathering methods. For investigating credit risk and factors affecting the probability of default, a quantitative approach is used to analyse the results from the aggregated database. Case study analysis entails a detailed and intensive analysis of a single case. In this regard, a case may be referred to a single organisation, country or industry (Saunders et al., 2009). The distinguishing feature of this thesis, as a case study in several countries, would be its focus on a bounded situation. The data for P2P lending industry is rather scattered and does not share common characteristics. Therefore, this study used the USA and EU regions as different case study analyses. However, this strategy might hinder the strength of this research in terms of generalisation. Nevertheless, concentration on a narrow aspect of the topic may serve as a strength rather than weakness. Limitations of the current study in terms of generalisation of findings in a broader geographical context are duly mentioned in 'Conclusion' chapter of this thesis.

4.4 Research methods

The existing literature allowed the author to identify the influential theoretical and empirical studies that identify factors influencing credit risk in traditional and alternative finance. This study bases the methodology on core relevant theory, namely the asymmetric information theory as a rationale behind the existence of adverse selection and moral hazard in P2P lending market. This theory was stipulated in the respective sections of Chapter 1 (Introduction) and Chapter 3 (Literature review) of this thesis.

However, as it is mentioned in the first chapter of this thesis, P2P lending market, as the novel channel of financial markets, was not fully explored in existing studies. Nevertheless, P2P lending market has certain modern characteristics that distinguish it from traditional financial markets. Thus, such factors as inflation, interest rate and economic downturn take a fundamental role in the analysis of this study. Following the propositions of existing studies in traditional finance, this thesis takes into account the consistency of determinants affecting the credit risk with several external variables that were not considered in earlier studies on P2P lending market.

This study explores the secondary research studies and the tendencies in mainstream literature as its first research instrument. The available literature on the topic is extremely limited in terms of peer-reviewed journal articles. Therefore, this study extends the review of existing literature beyond the journal articles and includes the research studies in newspapers, industry reports and websites. This helps to gain an insight into the current issues of P2P lending market. It also forms the backbone of factors used as independent and control variables. Further, the study conducts a descriptive analysis of existing data on loans issued by Lending Club (USA) over the last decade. Empirical analyses in Chapters 5-7 are based on the regression analyses that form the main research instrument of this study. Regression analyses test hypotheses which were developed in sections 3.5 and 3.6 of the Literature Review chapter. This chapter also explains the regression methods and variables used in this study.

The most important aspect that is considered is the triangulation in methods. The need for triangulation is largely reflected by the research philosophy and approach. Triangulation methodology reflects the use of more than one research technique (method triangulation) and/or data collection method (data triangulation) in research (Silverman, 2010). The use of more than one research technique and method is then used for cross-validation of research findings (Saunders et al., 2009). It is also reflected from the limited availability of the literature that put constraints in cross-validating the main results of this research project. Following realism, the study should conduct multilevel analysis and attempt to triangulate for extracting credible data (Bryman & Bell, 2011). By contrast, case studies are inclined to have limitations to both external validity and generalisability. These limitations are mostly eliminated by the use of multiple data collection techniques and triangulation of data analysis (Bryman & Bell, 2011). Accordingly, triangulation allows for increasing the reliability of the study and eliminate inherent weaknesses.

In this regard, triangulation involves cross-checking, comparing and contrasting various results that utilise different methods, and generate balanced conclusion (McNiff, 2016). Following the mainstream literature (Lloyd, 2011), this study cross-checks the results using different analytical techniques and compares the results with existing literature. For instance, the results from regression analysis are reported in conjunction with robustness tests. Moreover, the findings of empirical analysis in Chapter 5 (based on LendingClub loan-book) are cross-examined in the empirical analysis of Chapter 6 (based on the loan-book from two platforms in the EU).

4.5 Theoretical considerations based on traditional finance

Considering that the P2P lending industry is at its very early stage, the regression model was chosen accordingly, with a decent level of flexibility. The model aims to identify the determinants (mainly economic factors) of credit risk in P2P lending market. Review of existing literature indicated that both theoretical and empirical literature is not enough for building full methodological foundations of this study. Prior studies of Hu and Yang (2014), and Shi and Guan (2016) lend theoretical frameworks from traditional finance and borrow the concepts from venture capital and angel investments. Lukkarinen et al. (2016) raise the importance of this approach of drawing on research from adjacent funding industries in terms of its usefulness in evaluating the performance of alternative investment practices. Thus, this thesis referred to the literature in the closest available industry sector, namely venture capital and angel investments.

Research studies in the area of venture capital investments have been developing during the last two decades. As such, these studies have a solid conceptual framework proven via robust empirical analysis. Prior studies on both crowdfunding and P2P lending rely on a theoretical framework derived from venture capital, too (e.g. Mollick, 2014; Iyer et al., 2015; Lukkarinen et al., 2016).

The main aspect of the conceptual framework for this research project was drawn upon the theory of asymmetric information (section 1.6). Most of the research on P2P lending, as well as venture capital and angel investments, referred to this theory as the backbone of interest rate and funding success determination. The theory that was theoretically conceptualised by Akerlof (1970) refers to signalling as the mitigation mechanism for asymmetric information. In alternative financing markets such as P2P lending, signalling is significantly important, as each of the platforms brings together complete strangers into financing activity. From the investors' perspective, signalling tools have been widely examined in terms of determination of interest rates and funding success for borrowers in P2P lending platforms (Lin & Viswanathan 2016, Wei & Lin 2016 and Freedman & Jin 2017). However, no study explored platform success from the perspective of agency theory.

The success of the P2P lending platform is tied to the proper understanding of agency theory to a greater extent than the traditional financing practices. P2P lending operates under heavy reliance on signalling mechanisms such as regulation, credit rating and public financial reporting. As such, P2P lending platforms offering more transparency by being publicly listed or regulated could have better performance. However, no study explored platform success from the perspective of information asymmetry. Therefore, signalling can be used to examine the P2P lending platforms' transparency and efficiency as a whole.

Asymmetric information also creates 'moral hazard' problem where agents are to undertake activities that are not at the best interest of principal. In the case of P2P lending, agents (lending platforms) may increase the riskiness of their loan portfolio if faced with the poor quality. Investors (principal) being unaware of these hazardous activities may suffer from poor investment decision ('adverse selection'). This proposition has been largely investigated in traditional financing services and indicated that banks tend to increase their non-performing loans when faced with low credit quality (Keeton & Morris 1987, Messai & Jouini 2013 and Ghosh 2015). This study, relying on this theory considers default loans and late loan payments as the dependent variable. Credit ratings of borrowers (signalling) and economic indicators (financial accelerator and life-cycle consumption theory) are used as independent variables.

The models of traditional finance may also be applicable for the case of alternative investments, as indicated in Lukkarinen et al. (2016). The most prevalent and applicable theories are financial accelerator (Bernanke & Gertler 1989 and Kiyotaki & Moore 1997) and life-cycle consumption models (Lawrence, 1995) that relate business cycles with financial intermediation. Bernanke and Gertler (1989) and Kiyotaki and

Moore (1997) applied financial accelerator theory in their studies of traditional financial markets and posit that borrowing becomes more difficult and expensive during a recession because of the increased external finance premiums. On the other hand, the life-cycle consumption theory directly relates business cycles with financial intermediation and states that the ability to default when income is low allows people to borrow against an uncertain future (Lawrance, 1995). This enhanced level of borrowing increases consumption rates and debt of borrowers (Lawrence, 1995). These models have been empirically tested in both US (Keeton, & Morris 1987; and Gambera, 2000) and European markets (Klein, 2013 and Skarica, 2014). Gompers and Lerner (1998), and Félix, Pires, and Gulamhussen (2013) empirically tested these theories in alternative investment markets by proposing that stock market development, GDP growth and unemployment have an impact on the development of venture capital investments. These theories, on its turn, are directly related to the first, second and third questions of the current study and built upon the hypotheses in section 3.5. These models relate both overall lending volume and probability of default to economic activity.

Therefore, this thesis uses financial accelerator, life-cycle consumption and asymmetric information theories, which have been extensively tested in traditional financial markets (and in alternative investment markets to a lesser extent), to motivate the key research questions proposed in Introduction Chapter (Chapter 1) of this thesis. Using these theories, this study investigates macroeconomic, borrower specific and country/regional aspects of P2P lending markets from the perspective of their respective impact on loan quality and credit risk.

4.6 Model description

Modelling of the empirical study of this study is comprehensively described in this section based on the number of theoretical and empirical studies from traditional finance and economics. This section provides the rationale behind each of the explanatory variables under consideration (interest rate and inflation) with an elaborative theoretical explanation. Proposed regression method and equations mainly aim to identify the determinants of P2P loan defaults. STATA software is used for the empirical analysis of this thesis.

4.6.1 Interest rate and default

Borrower's decision to default on a loan depends on borrower's ability to repay the loan interest after taking into account household utility. Subject to budget constraint borrowers draw their optimal consumption level (Campbell & Cocco, 2015). Accordingly, consumption equals the expected household net disposable income minus payments for servicing debt at time *t*. (Mian, Sufi, & Verner, 2015).

$$c_t = y_t - rd_t \qquad [1]$$

where,

$c_t - household\ consumption\ at\ time\ t$

$y_t - household\ net\ disposable\ income$

$r - interesst\ rate\ on\ a\ loan$

$d_t - net\ outstanding\ household\ debt\ at\ time\ t$

This study defines the minimum consumption level required by a household as $\underline{c} \geq 0$ which can be interpreted as subsistence consumption (Adam & Grill, 2017; Bocola, Bornstein, & Dovis, 2019). The household will decide to default on an outstanding debt when consumption falls below the minimum consumption level ($c_t < \underline{c}$). A household may not have the ability to pay when faced with certain shocks like loss of a job (unemployment) or adverse economic outlook (Laufer, 2018). Thus, the probability of default is the function of interest rate (*r*), change in outstanding debt (Δd) and household income (Δy).

$$Prob(c_t < \underline{c}) = \mathcal{F}(r, \Delta d, \Delta y, X) \qquad [2]$$

where *X* is a vector of control variables representing platform and economy specific conditions.

4.6.2 Inflation rate and default

Following Parul and Leo (2010), the author can rearrange equation [1] and derive the following expression for modified household debt to income ratio (ψ):

$$\psi = \frac{rd_t}{y_t - c_t} \qquad [3]$$

Household consumption (c_t) can be identified as the product of the general price level (p_t) and the amount of goods consumed (q_t^c):

$$c_t = p_t q_t^c \qquad [4]$$

By replacing the product of interest rate and outstanding debt (rd_t) with a simplified expression of debt service per period (S_t) the author arrives at the following modification of equation [3]:

$$\psi = \frac{S_t}{y_t - p_t q_t^c} \qquad [5]$$

At the level of $\psi=1$ household income is just enough to service the outstanding debt. Under the assumption of no income beyond y_t (no household savings), $\psi > 1$ infers that the borrower will likely default. At this level household will not have sufficient income to service the debt. Accordingly, the probability of household default is identical to the probability of the ratio (ψ) going beyond 1. Equation [5] also implies that the ratio (ψ) is the positive function of the price level (p_t).

Thus, the probability of default can be expressed as the function of change in the price level (Δp), debt service (ΔS), household income (Δy) and vector of control variables (X).

$$Prob(\psi > 1) = \mathcal{F}(\Delta p, \Delta S, \Delta y, X) \qquad [6]$$

4.6.3 Baseline regression model

In chapters 5 and 6, this thesis examines the linkage between default (delinquency) rates and interest rate and inflation in panel data framework. Chapter 5 considers these associations in the regional context using the LendingClub data based on individual states of the USA. Chapter 6 empirically analyses these relationships in the cross-country context based on the loan-book data of Bondora (Estonia) and Mintos (Latvia). This study adopts the panel data regression model (in Chapter 5 and 6) in order to account for the dynamics of individual states within the US, and individual countries within Continental Europe.

The general panel data regression model can be written as:

$$y_{it} = \alpha + \beta \ X_{it} + \lambda_t + v_i + e_{it} \qquad [7]$$

Where, y_{it} is the dependent variable and X_{it} is the vector of independent variables. So, it can be said that y_t is explained by independent variables. The e_{it} is an idiosyncratic error term that represents random observation-specific unobserved factors with zero-mean ($E(e_{it})=0$). The β is the independent variable coefficient that reveals the magnitudes of independent variables' effects on y_{it}. The α is the intercept of the regression model. Time and individual-specific effects are represented by λ_t & υ_i respectively.

The data used in this study are diverse in terms of its time variability[9] that increases the importance of panel data regression method. In this regard, this study mainly uses cross-country panel data via Pooled Ordinary Least Squares regression method at its initial stage. However, this method of regression is a simplistic extension of Ordinary Least Squares and largely unsuitable for panel datasets. Wooldridge (2002) motivates this proposition by the failure of Pooled Ordinary Least Squares to take into account the cross-section and time-series nature of the data. In this regard, the market is growing with different pace in various states of the US with specific preconditions. Therefore, in this particular case of this study, the major potential problem with Pooled Ordinary Least Squares method would be the neglect of distinguishing features between borrowers in various state areas (or countries) under consideration. Thus, by merging all P2P lending capacity by pooling, the regression analysis has to disregard heterogeneity (i.e., individual effects of states/countries) that may be present between them.

Consequently, following the results of the initial regression method, the study would go further by employing the different model for inspecting the reliability of results from the initial model. Two general types of regression methods for panel datasets exist that deal with this specific issue. These models are Fixed Effects (FE) or Least Squares Dummy Variable (LSDV) and Random Effects (RE) estimation. In RE model error term υ_i in equation [7] is assumed to be random effects compared with the FE model where it is fixed effects (Wooldridge, 2009).

The study aims to determine one of the two models (FE vs RE) the choice of which would define the credibility of the findings or distort forthcoming results. Following the proposition of Greene (2012) the major reasoning on the choice of FE or

[9] Refer to section 4.7 of this chapter for data and variable descriptions

RE is whether the unobserved individual effect embodies elements that are correlated with the regressors in the model, not whether these effects are stochastic or not. Thus, the choice of one of the methods is mostly subject to the nature of the dataset. For example, in Chapter 5, dissimilarities between the borrowers in different states may influence the 'delinquencies' that is the dependent variable. If this is the case, the random-effects model is preferred (Greene, 2012). Furthermore, RE method permits including time-invariant variables, while FE method enthrals these variables into the intercept (Baltagi, 2008). Thus, as study employs time-invariant variables (eg. labour force, population, state political party affiliation), the structure of the dataset and essence of the study prefer the use of RE method. Though the structure of the dataset and essence of the study prefer the use of RE model, this study compares the results of RE and FE estimation methods for their validity. Scholars suggest using a Hausman test before deciding the use of FE or RE methods (Greene, 2012).

At the same time, it should be taken into account that this study uses different datasets at different stages of the research. Accordingly, the choice of the methods varies from one dataset to another. Corresponding regression methods are further specified in respective empirical chapters where applicable (Chapters 5, 6 and 7).

The first regression equation is based on equation [2] and can be generally represented as equation [8] which aims to estimate defaults (delinquencies) as a function of interest rate.

$$\mathrm{D}_{\mathrm{i,t}} = \alpha + \beta_1 r_{\mathrm{i,t-6}} + \beta_2 \mathrm{L}_{i,t-12} + \beta_3 \mathrm{X}_{i,t}^{Platform} + \beta_4 \mathrm{X}_{i,t-6}^{Macro} + \beta_5 \mathrm{X}_{i,t}^{Demographics} + \beta_6 \mathrm{X}_{i,t}^{Technology} + \beta_7 \mathrm{X}_{i,t}^{Business} + \beta_8 \mathrm{X}_{i,t}^{Politics} + \lambda_t + \upsilon_i + e_{it} \quad [8]$$

$\mathrm{D}_{\mathrm{i,t}}$ – Variable indicating the defaults (delinquencies) among P2P lending platform borrowers in state/country *i* at time *t.* This variable is represented by bad loans/probability of default, as explained in the data and variables' description section of this chapter (section 4.7.1).

$r_{\mathrm{i,t-6}}$ – Average interest rate set for issued loans by the P2P lending platform at time *t-6* in state/country *i.* Calculated from the loan-book of the respective P2P lending platform based on equation [12].

$L_{i,t-12}$ – Variable indicating the previous period (*t-12*) volume of P2P lending in state/country *i*. It reflects on borrower's outstanding debt as per the equation [2].

$X_{i,t}$ – vector of control variables. These variables represent borrower-specific, macroeconomic conditions, demographics and other aspects of each state/country *i* at time *t* under consideration. The vector of variables also includes earnings and GDP growth in the state/country to reflect on household income as per the equation [2]. Further variable descriptions are presented in the respective sections of empirical chapters.

Second regression equation resembles upon equation [6] and generally represented as equation [9]. It aims to estimate defaults (delinquencies) as a function of inflation. Unlike equation [8] it has a variable indicating a change in the price level in state/country *i* at time *t-6* denoted as $p_{\mathrm{i,t-6}}$.

$$D_{\mathrm{i,t}} = \alpha + \beta_1 p_{\mathrm{i,t-6}} + \beta_2 L_{i,t-12} + \beta_3 X_{i,t}^{Platform} + \beta_4 X_{i,t-6}^{Macro} + \beta_5 X_{i,t}^{Demographics} + \beta_6 X_{i,t}^{Technology} + \beta_7 X_{i,t}^{Business} + \beta_8 X_{i,t}^{Politics} + \lambda_t + \upsilon_i + e_{it} \quad [9]$$

It should be noted that explanatory and macroeconomic control variables are lagged by six periods to reflect on delayed response of delinquencies to external shocks. It is well documented that changes in macroeconomic determinants affect the quality of loans with different time lags (Ali & Daly, 2010; Norden & Wagner, 2008). Specifically, real gross domestic product, nominal interest rate and inflation enter into causation with a lag of at least two quarters (Bocola et al., 2019; Chen & Wu, 2014). From a theoretical point of view based on business cycles, households' ability to repay their loans are affected after their income gets a hit (with a lag) from macroeconomic changes (Rubaszek & Serwa, 2014). Macroeconomic indicators like GDP growth are the lagging indicators of the business cycle. Thus, this study uses lagged observations of explanatory and macroeconomic variables by two quarters, which will translate into six months lag in the database of this thesis. Loan volumes are lagged by one year (12 months) because of the loan assessment cycle (monitoring process) experienced in banks that is also a characteristic procedure in P2P lending platforms. As per the monitoring cycle, a financial institution assesses and issues a loan; during the lifespan of the loan, it undertakes the monitoring and decides whether to lay off credit risk in the case of likely default. A half duration of this cycle for consumer loans is around one year (Jokivuolle & Virén, 2013; Khieu, Mullineaux, & Yi, 2012). This study does not use lagged observations of other control variables as they generally consist of time-invariant or yearly observations.

4.7 Description of data and variables

Chapters 5 and 6 investigate the impact of interest rate and inflation rate on defaults (delinquencies) within the context of P2P lending platform based in the USA and Continental Europe. Unlike banks, there is a lack of international or local authority that regulates P2P lending activities, and that collects information on them. Therefore, data were collected and compiled from several sources for this study. Within the framework of this study, the author used the P2P lending platform data from LendingClub (USA), Bondora (Estonia) and Mintos (Latvia). Respective empirical chapters provide a broader explanation of the database and its aggregation, in line with the detailed description of specific variables. This section covers the general description of the variables employed. For this part of the chapter, the study discusses the variables applied, both the independent and dependent variables. Then, the study describes the procedure of overcoming endogeneity with the instrumental variable specification.

4.7.1 Dependent variables

There has been a considerable amount of studies investigating consumer credit defaults and delinquencies in traditional financial institutions. There are only a couple of studies (Serrano-Cinca, et al., 2015; Wei and Lin, 2017) considering these factors in P2P lending market. They generally follow existing definitions and concepts from traditional literature. While exploring the linkage between delinquency and determinants, this study follows the concepts of existing literature in defining delinquencies. Following Kim, Cho, and Ryu (2018); Wadud, Ahmed, and Tang (2019), this study defines delinquent loans as those in grace period with 30+ or more days due and still incurring interest. Default loans are the combination of loans with the status in default and all the charged-off loans. Default loans if combined with delinquent loans, provide a broader definition of bad loans that better characterise financial distress than defaults. This approach follows the treatment of financial distress and insolvency of borrowers among traditional financial institutions via non-performing loans (Louzis, 2012; Ghosh, 2015).

This study relies on a broader definition of bad loans for using as a dependent variable in empirical regression equations [8] and [9]. LendingClub classifies loans into the categories of current, fully paid, default, in grace period, overdue 16-30 days, overdue 31-120 days, and charged-off. Mintos classifies loans into similar categories as LendingClub (Mintos 2020). Bondora places loans under a ‘cure period’ after two scheduled payments lapse without payment. After the ‘cure period’, the loan is assigned with the ‘default’ status, and the platform initiates the collection/recovery process (Bondora, 2016). In this regard, defaulting in Bondora loan book occurs in approximately one month following the last scheduled payment. Accordingly, this study calculates bad loans for state/country *i* at time *t* as per the equation [10].

$$Bad\ Loans_{i,t} = Default_{i,t} + Chargedoff_{i,t} + Overdue_{i,t}^{31-120\ days} \quad [10]$$

As the count of loans might not be proportional to the total dollar amount of bad loans, the study runs separate regressions using loan count and dollar value of loans. As the last payment date and issue date of the loans are different, bad loans are aggregated separately from the rest of the database.

However, absolute values of bad loans might provide a distorted picture of financial distress for P2P lending borrowers. Industry experienced high growth rates during the last ten years, so did the bad loans. Accordingly, there is an inherent upward trend in absolute values of bad loans. Following Câmara, Popova, and Simkins (2012), for analysis, this study uses the probability of default (PD) as a key credit risk parameter for estimating losses in P2P lending market. In line with the existing literature (Ali & Daly, 2010; Fungáčová, Shamshur, & Weill, 2017; Jakubík & Schmieder, 2008; Simons & Rolwes, 2009) this study calculates PD as the following equation:

$$PD_{i,t} = \frac{Bad\ Loans_{i,T}}{Loans_{i,t}} \quad [11]$$

T – last payment date for the bad loans, while *t* – issue date for the loans. This study uses PD for the baseline regression analysis and reports results in respective chapters (Chapters 5-7). Regression results for absolute values of bad loans (bad loan count and total dollar value of bad loans) are provided in Appendix B.

4.7.2 Main independent variables

Interest rates: Theoretical literature indicated that higher interest rate creates more problems for the client in repaying his debt. Studies have provided mixed evidence on the association between the interest rate and loan delinquencies in traditional financial markets. An increase in the interest rate limits the ability of borrowers to meet their debt obligations. Thus, a surge in the interest rate increases loan delinquencies and hence NPLs (see, e.g. Beck, 2013; Espinoza & Prasad, 2010; Louzis, Vouldis, & Metaxas, 2012). Hence, a higher interest rate should influence the probability of default in the same way. If it is considered that low-interest rates are usually connected with recession period, and if it is assumed that PD is negatively correlated with GDP growth, the relationship between interest rates and PD might be negative as well. On the other hand, Goel and Hasan (2011), Jakubík (2006) and Virolainen (2004) demonstrated that higher default rates were observed in economies with lower interest rates. The study by Ghosh (2015) found an insignificant relationship between the real interest rate and NPLs among US financial institutions. We sought to formulate a hypothesis on whether high-interest rates have a predictive relationship with loan delinquencies among P2P lending platform borrowers.

In the analysis, this study uses average interest rates (AVEINTRATE) set for the loans as per the equation [12].

$$\text{AVEINTRATE}_{i,t} = \frac{\sum_{k=1}^{k=n} {}_{i,t}r_k}{n} \qquad [12]$$

Where, ${}_{i,t}r_k$ – is the k's loan issued in state/country *I* at time *t*, *n* – is the number of loans issued at time *t* in state/country *i*.

Inflation: Changes in price level is analysed in Chapters 5 and 6 as another important determinant of PD. Both theoretical and empirical literature provides mixed results for inflation as a determinant of PD. Studies on the role of inflation in determining financial lending and consequent loan defaults have been prevalent in the financial literature. From the theoretical perspective, inflation reduces the real value of outstanding debt and interest payments (Chambers, Garriga, & Schlagenhauf, 2009). High inflation even stimulates more household spending and reduces unemployment (known as the Phillips curve), thus producing a negative relationship between inflation and loan delinquencies. In contrast, as a result of 'wage stickiness', the value of real income is eroded by inflation, thus reducing the available funds of borrowers. Debt repayments become more difficult, ultimately leading to a deterioration of the quality of the loan portfolio (Theong, Osman, & Yap, 2018). Based on the above theoretical arguments, we expect the coefficients for inflation rate to be positive.

The inflation rate is used as a proxy for seasonally adjusted consumer price index for each period and state/country under consideration. State-level inflation data for USA are not available, and this study uses the percentage change of the Consumer Price Index (CPI) of the largest urban centre either in the state or closest to that state. If the data are not available for the closest urban centre, this study uses regional CPI data as a proxy. Chapter 6 uses country-level CPI data which is available for all countries under consideration. The monthly inflation rate (INFLATION) for state/country *I* is calculated as in the equation [13].

$$INFLATION_{i,t} = ln\left[\frac{CPI_{i,t}}{CPI_{i,t-1}}\right] \qquad [13]$$

4.7.3 Control variables

This study also uses a broad array of control variables to account for economic, demographic and technology-specific characteristics of each state/country[10]. Existing literature provides robust evidence that general economic development significantly affects the credit risk of financial institutions (Dinger, 2009; Valla & Saes-Escorbiac, 2006). Evidence of the positive impact of economic development on alternative financial markets is also present in studies of Khrawish, Siam and Jaradat (2010) and Mollick (2014). Thus, this study includes GDP growth, economic sentiment indicator and unemployment rate as proxy variables for economic development. Jagtiani and Lemieux (2018), Tanda (2019) and Thakor (2020) indicate a direct relationship between traditional financial markets and alternative lending markets. Change in stock market index (used in Chapter 6) is another economy-specific variable used in this study to represent traditional financial markets.

[10] Chapter 5 analyses the USA P2P lending market within the context of individual states. Chapter 6 does it in the context of EU countries.

Existing studies on P2P lending extensively use borrower and loan characteristics in estimating loan funding success and default (Cai, Lin, Xu, & Fu, 2016; Galema, 2020; Serrano-Cinca, Gutierrez-Nieto, & Lopez-Palacios, 2015; Wei & Lin, 2016). The loan duration is expressed in months and provide lenders with additional information about the default risk of the loan. Loans with shorter durations tend to signal quality by reducing asymmetric information problems and increasing the probability of selection (Menkhoff, Neuberger, & Rungruxsirivorn, 2012; Steijvers & Voordeckers, 2009). The loan amount is another important indicator of solvency risk where the larger loan amounts are riskier to the extent that they increase default incentives. This study expects that the loan amount is negatively related to the probability of default. Traditional forms of finance segregate offers of financing arrangements on the basis of age and gender (Bellucci, Borisov, & Zazzaro, 2011; Blanchflower, Levine, & Zimmerman, 2003). P2P lending markets are more inclined towards market mechanisms and liberal approaches to loan selection. Therefore, investors in these platforms may be less prone to bias with respect to age and gender in their investment allocation (Cumming, Meoli, & Vismara, 2019; Duan et al., 2020). This study includes the age[11] characteristics of borrowers with the expectation that the effect on the probability of success is unclear. The reader may refer to the conceptual framework (section 1.6), review of the literature and theoretical considerations (section 4.5) for further arguments supporting the use of variables. This section further elaborates some of the important control variables used in this study. Table 5.1 and Table 6.1 in chapters 5 and 6 provide a complete list of variables with their descriptions and sources.

Loan Volume: The study uses monthly loans issued at each state/country as one of the platform-specific control variables. All of the empirical analyses use log differences of loans issued, as log differencing eliminates drift and trend component of non-stationary data. At the same time, log differencing allows analysing the growth of the market rather than the size at a certain period. Log differences of monthly loans issued are obtained by taking the natural logarithm of the monthly loan volumes (LOANVOLUME) at each state/country *I* at time *t*.

[11] Gender is used in Chapter 7 as one of the control variables.

$$\text{LOANVOLUME}_{i,t} = ln\left[\frac{\text{LOANVOLUME}_{i,t}}{\text{LOANVOLUME}_{i,t-1}}\right] \quad [14]$$

Debt-to-income ratio (DTI): The debt-to-income score of the borrower (DTI) is an important indicator used in lending for signalling borrower solvency. This ratio is defined as the monthly debt payments on total debt obligations, excluding mortgage and the loan currently requested via P2P lending platform, divided by self-reported monthly income. The author calculates monthly state-wide/country-wide average DTI score as in equation [15].

$$\text{DTI}_{i,t} = \frac{\sum_{k=1}^{k=n} {}_{i,t}DTI_k}{n} \quad [15]$$

Where, ${}_{i,t}DTI_k$ – is the DTI score of *k*'s funded loan listing issued in state/country *i* at time *t*; *n* – is the number of successful listings of loans from P2P lending platform at time *t* in state/country *i*.

Low-risk DTI ratio falls in the range between 0 and 0.4 (DTI ratio ∈ [0, 0.4)), where the upper bound is a healthy level of leverage recommended by LendingClub. Existing leverage of the borrower is considered to be high risk between 0.4 and 1 (DTI ratio ∈ [0.4, 1.0]). A borrower with the ratio higher than 1 is considered to be insolvent (DTI ratio ∈ (1.0, ∞)).

Gross Domestic Product (GDP): Economic development and wellbeing are best associated with GDP in empirical studies. Existing studies on crowdfunding platforms highlighted GDP growth as an important factor in the industry's development (Mollick, 2014; Dushnitsky et al., 2016). This study uses each state's (country's) contribution to the percentage quarterly real GDP growth (GDP_CONTR) as a proxy for economic development.

4.8 Estimation method with instrumental variables (IVs)

Baseline regression analysis, as presented in equations [8] and [9] come with an inherent shortcoming that is endogenous explanatory variables. The panel data method that used in this study does not solve the problem of time-varying omitted variables that are correlated with the explanatory variables. This problem could be solved by suitable proxy variables which are not available in the case of this study. This study takes an approach of using instrumental variables (IV) to solve this inherent endogeneity problem in the baseline regression models of Chapter 5 and 6.

This thesis relies its empirical estimation on the procedure of the two-stage generalised method of moments (GMM) estimation. In line with Hakura and Cosimano (2011) the first stage regression for interest rate (INTRATE) is represented in the form of the previous-period unemployment rate (UNEMRATE) and earnings (EARNINGS) combined with control variables. Second stage regression then employs PD as the depended variable with an estimated interest rate as an explanatory variable. Concluding from the proposition of Hakura and Cosimano (2011) and relying on Barajas, Chami, Espinoza, and Hesse (2010), the specification of the relationship between PD and determinants is presented in Figure 4.1 and Figure 4.2.

As per the specification, the two-stage regression estimates the interest rate and inflation rates with instrumental and control variable. The estimates consequently define the explanatory variable. As per Hull's (2012) argument that financial institutions simultaneously choose the optimal amount of the loan rate, and quantity of loans, GMM estimation procedure deemed to be appropriate for this case. Following the works of Hall (2005); Hayashi (2011) this study uses the heteroskedasticity – autocorrelation-consistent (HAC) standard errors. Generally, the model allows estimating the effect of determinants on PD in a context which simple regression analysis could not accomplish.

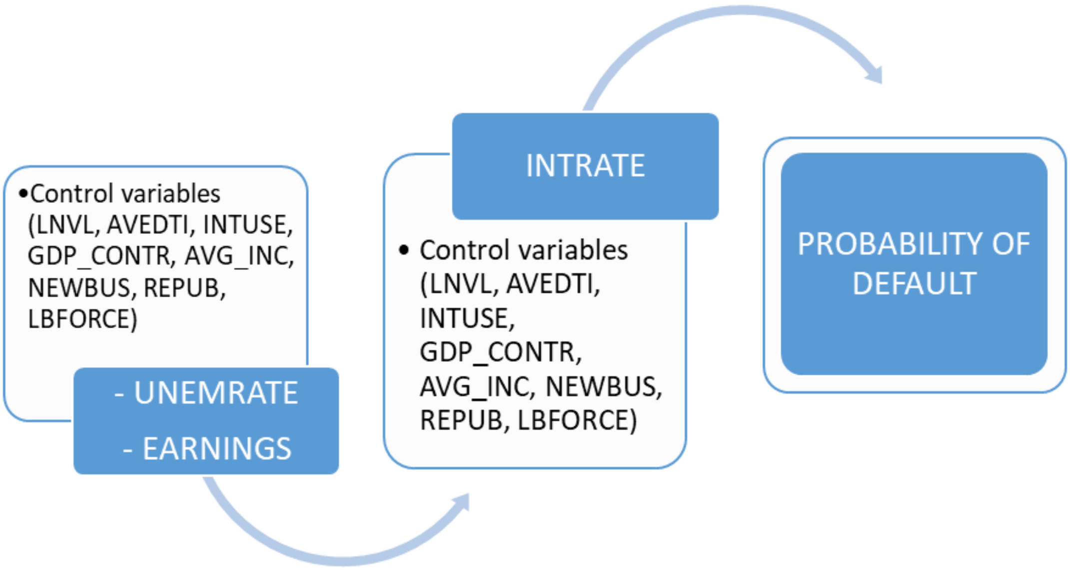

Figure 4.1: IV model specification with interest rate as explanatory variable

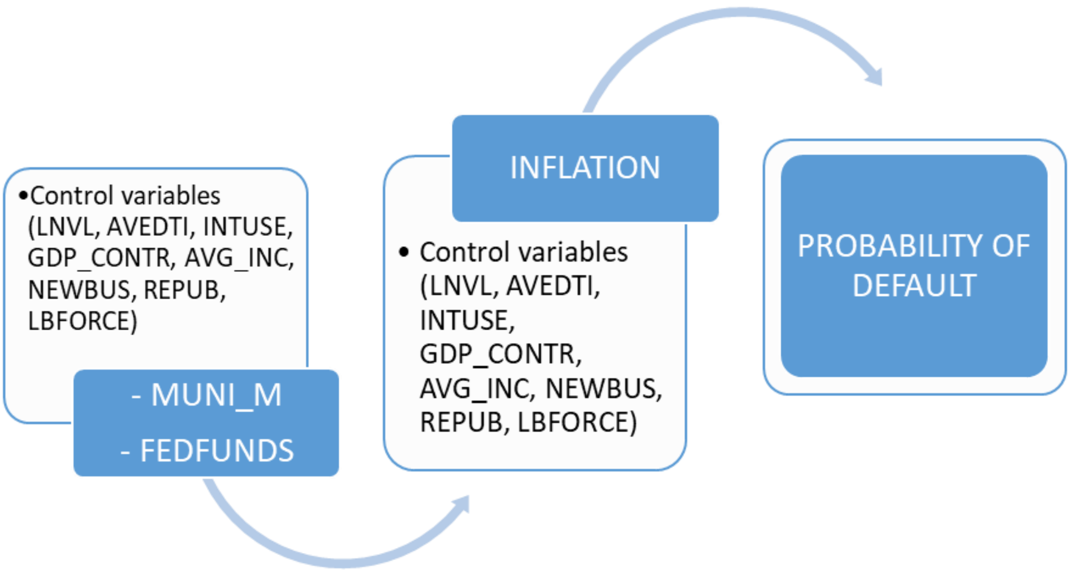

Figure 4.2: IV model specification with inflation as explanatory variable

4.9 Summary of the chapter

This chapter presented the data used and the methodology employed in this study. It started with introducing the research of philosophy, approach and strategy. This chapter also described the research methods and theoretical considerations related to the empirical chapters (Chapters 5-7). The model description section of this chapter elaborated the baseline regression method and the main explanatory variables (interest rate and inflation). Then, this chapter described the variables used in this thesis, together with their definitions and measurements. The baseline regression model of the study is tested using instrumental variables estimation, which is described in section 4.8.

This chapter is followed by three empirical chapters that use different sets of data sets and explore the respective research questions, as outlined in section 1.8. The data set, sampling method and regression models are further elaborated in the following three empirical chapters.

Chapter 5:

Macroeconomic Determinants of Loan Defaults in P2P Lending Market: Empirical Analysis Based on LendingClub (USA)

5.1 Outline of the chapter

This chapter provides a detailed description of the result and interpretation of the research work based on the analysis of LendingClub (USA) loan-book. The first part of this chapter consists of a descriptive analysis of the data set. Descriptive analysis is followed by statistical tests and regression analysis.

5.2 Description of data and sampling

This chapter uses secondary data from LendingClub loan-book database. The scope of this chapter covers the loans issued by LendingClub and timespan ranges from 2008 to 2018. However, the data set consists of unbalanced panel data, where certain observations for several states at certain periods are missing. LendingClub provides its comprehensive loan-book with diverse features of each loan and loan holder. At the initial stage of the research, this study combined LendingClub loan-books from 2008 to 2018 that amounted to a single database consisting of over 2 million observations. This study aggregated all information on issued loans by month and state of origination. The author assigned missing values if there were no loans issued in a state at a particular month. Loan data were then aggregated with state-specific variables obtained from other sources. For example, this study added data on real GDP for each state in the USA from the Bureau of Economic Analysis (BEA) database. Some of the variables are not available as monthly data, for which the available data with most frequent observations were used. For example, only quarterly data are available for real GDP numbers. This study duplicated and assigned quarterly observations to their respective monthly periods. In the case, if data were not available for certain variables, the author used their closest proxies as an alternative. Inflation is one of these variables, which is not reported on a state-wide basis. However, the US Bureau of Labor Statistics reports monthly Consumer Price Index (CPI) for most of the urban centres and regions of the USA. This study used this data set as a proxy for respective observations of state-wide inflation rates. All monetary values are presented in United States dollars (US$). The reader can access the supplementary material attached to this thesis for viewing the database before and after the aggregation[12]. The snapshots of the database before and after the aggregation are presented in Appendix D. Table 5.1 describes all variables used in this chapter.

The final sample consists of 5834 valid observations. Some variables have missing values because of non-availability of data, thus reducing the sampling size (N) in regression results. The number of delinquent loans for some states at certain periods was equal to zero or very close to zero. This aspect of the sample data set further reduced the sampling size in the analysis. As the author reduced the sample size because of incomplete data, it might create the sample that is not the representative of the population. The delinquency rates in the sample data set can be lower than delinquency rates in the reference population of USA P2P lending market. The problem of 'choice-based sample' has been a well-known problem since early studies of default probabilities (Zmijewski, 1984). The study uses the random bootstrap technique to eliminate the 'choice-based sample' and obtain robust estimates of the relevant coefficients. Following Chernick and LaBudde (2014), and Tibshirani and Efron (1993), this study reduces the sampling bias by randomly selecting the observations (with replacement) from the database. The process is repeated the sampling procedure with 100 iterations for each regression model and calculate average coefficients for robust estimates. The bootstrap procedure warrants that estimates are not affected by under-weighting of delinquency rates in the sample compared to the actual national delinquency rates.

[12] Data are available from the author upon reasonable request and with permission of the third party where applicable.

Table 5.1: Description of variables used in Chapter 5 analysis

Variable	Description of variable	Source
Dependent variables		
BADLOANSVOL	Total volume of defaulted and late loans at state *i* at time *t* as per equation [10] (monthly, in dollars)	*LendingClub*
BADLOANSCOUNT	Number of defaulted and late loans at state *i* at time *t*. (monthly)	*LendingClub*
PD	Probability of default as in equation [11]. Share of bad loans in total loans at state *i* at time *t*. (monthly)	*LendingClub*
Explanatory variables		
AVEINTRATE	Average interest rate on loans issued by Lending Club at state *i* at time *t* as per equation [12] (monthly, percentage points)	*LendingClub*
INFLATION	Monthly change in seasonally adjusted consumer price index for all goods by state as per equation [13] (percentage points, proxy by urban centres and US regions)	U.S. Bureau of Labor Statistics (BLS) www.bls.gov
Independent variables, $\boldsymbol{X^{Platform}}$ - platform-specific		
LOANCOUNT	The number of listed loans outstanding applied for by the borrowers at state *i* at time *t*. (monthly)	*LendingClub*
LOANVOLUME	Total volume of listed loans outstanding applied for by the borrowers at state *i* at time *t*. Lod differenced values as in equation [14] (monthly, in dollars)	*LendingClub*
AVEDTI	Average DTI score of borrowers at state *i* at time *t*. DTI score is calculated as a ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested Lending Club loan, divided by the borrower's self-reported monthly income. Monthly state-wide average DTI score calculated as in equation [15].	*LendingClub*
AVEINCOME	Average annual income of borrowers at state *i* at time *t*. Annual income is the combined self-reported annual income provided by the co-borrowers during registration (monthly, in dollars)	*LendingClub*
AVEREVOL	Average revolving line utilisation rate of borrowers at state *i* at time *t*. revolving line utilisation rate is the amount of credit the borrower is using relative to all available revolving credit. (monthly)	
Independent variables, $\mathbf{X}^{\boldsymbol{Macro}}$ – macroeconomic and country-specific variables		
GDP	Quarterly real GDP by state (millions of chained 2009 dollars)	Bureau of Economic Analysis (BEA) www.bea.gov
GDP_CONTR	Contributions to percentage change in real GDP (quarterly, percentage points)	Bureau of Economic Analysis (BEA) www.bea.gov
EARNINGS	Average weekly earnings of all employees at each state (monthly, in dollars)	U.S. Bureau of Labor Statistics (BLS) www.bls.gov
UNEMPLOYMENT	Number of unemployed labour force for each state (monthly)	U.S. Bureau of Labor Statistics (BLS) www.bls.gov
UNEM_RATE	Unemployment rate for each state (Monthly, seasonally adjusted, percentage points)	U.S. Bureau of Labor Statistics (BLS) www.bls.gov

FEDFUNDS	Monthly average of daily effective Federal Funds Rate. The federal funds rate is the interest rate at which depository institutions trade federal funds with each other overnight.	Federal Reserve Economic Data (FRED) https://fred.stlouisfed.org
MUNI_RATES	One-year municipal bond yields for each state (monthly average of daily yield rates)	*Bloomberg terminal, function key BVAL & MUNIC*
Independent variables, $\mathbf{X}^{Demographics}$ - variables representing demographic characteristics of states		
LABOR_FORCE	Labour force for each state (monthly number of population in labour force)	U.S. Bureau of Labor Statistics (BLS) www.bls.gov
RELIGIOSITY	Percentage of adults who say they believe in god by state (time-invariant)	Religious Landscape Study (2014), Pew Research Center
CHRISTIANITY	Percentage of adults who identify themselves as Christian by state (time-invariant)	Religious Landscape Study (2014), Pew Research Center www.pewresearch.org
Independent variables, $\mathbf{X}^{Technology}$ - variables representing 'technology' of states		
INTUSE	Number of internet users at any location by state for each year from 2008–2016 (yearly)	U.S. Census Bureau Census.gov
Independent variables, $\mathbf{X}^{Business}$ - variables representing business sentiments of states		
EMPL_EXPAN	Employment gained from expansions of businesses at each state (monthly)	U.S. Bureau of Labor Statistics (BLS) www.bls.gov
EMPL_BIRTH	Employment gained from establishment of businesses at each state (monthly)	U.S. Bureau of Labor Statistics (BLS) www.bls.gov
NEW_BUS	Number of established new businesses at each state (monthly)	U.S. Bureau of Labor Statistics (BLS) www.bls.gov
NEW_BUS_PROP	Share of established new businesses in total number of businesses at each state (monthly)	U.S. Bureau of Labor Statistics (BLS) www.bls.gov
Independent variables, $\mathbf{X}^{Politics}$ - variables representing political sentiment of states		
REP	Percentage of voters that voted for Republican candidate for each state (based on United States Presidential Election Results 2008, 2012 and 2016)	David Leip (2016) https://uselectionatlas.org
RED	Dummy variable: 1 – if the state voted for Republican candidate in General Election (based on United States Presidential Election Results 2008, 2012 and 2016)	David Leip (2016) https://uselectionatlas.org

5.3 Descriptive statistics

Table 5.2 provides the list of US states with the respective number of observations. Some states do not have observations for early periods in the database, as borrowers were not eligible for loans from LendingClub during this time. Currently, individuals residing in all states except for Iowa and the U.S. territories are eligible to borrow through LendingClub. There are very few observations from Iowa, which is the result of borrowers being registered in two states simultaneously during the lifespan of the loan. All observations from the state Iowa were removed in regression analysis.

Table 5.2: Number of observations by state and year

State / Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
Alabama	7	11	12	12	12	12	12	12	12	12	12	**123**
Alaska	4	7	10	12	12	12	12	12	12	12	12	**111**
Arizona	12	12	12	12	12	12	12	12	12	12	12	**131**
Arkansas	6	9	12	12	12	12	12	12	12	12	12	**119**
California	12	12	12	12	12	12	12	12	12	12	12	**129**
Colorado	12	12	12	12	12	12	12	12	12	12	12	**132**
Connecticut	10	12	12	12	12	12	12	12	12	12	12	**129**
Delaware	6	12	12	12	12	12	12	12	12	12	12	**121**
District of Columbia	7	12	12	12	12	12	12	12	12	12	12	**122**
Florida	12	12	12	12	12	12	12	12	12	12	12	**133**
Georgia	12	12	12	12	12	12	12	12	12	12	12	**133**
Hawaii	6	10	11	12	12	12	12	12	12	12	12	**117**
Idaho	3	0	0	0	0	1	1	0	11	12	12	**34**
Illinois	12	12	12	12	12	12	12	12	12	12	12	**128**
Indiana	0	0	0	0	2	12	12	12	12	12	12	**73**
Iowa	7	0	1	0	0	1	1	0	0	0	12	**10**
Kansas	12	11	3	12	12	12	12	12	12	12	12	**119**
Kentucky	6	12	12	12	12	12	12	12	12	12	12	**121**
Louisiana	8	12	12	12	12	12	12	12	12	12	12	**126**
Maine	0	0	0	0	0	0	1	4	12	12	12	**38**
Maryland	12	12	12	12	12	12	12	12	12	12	12	**132**
Massachusetts	11	12	12	12	12	12	12	12	12	12	12	**132**
Michigan	12	12	12	12	12	12	12	12	12	12	12	**126**
Minnesota	12	12	12	12	12	12	12	12	12	12	12	**126**
Mississippi	8	6	0	1	1	2	9	12	12	12	12	**69**
Missouri	12	12	12	12	12	12	12	12	12	12	12	**132**

Montana	5	6	11	12	12	12	12	12	12	12	12	**114**
Nebraska	3	0	0	0	1	2	0	6	12	12	12	**46**
Nevada	10	12	12	12	12	12	12	12	12	12	12	**125**
New Hampshire	6	10	12	12	12	12	12	12	12	12	12	**121**
New Jersey	12	12	12	12	12	12	12	12	12	12	12	**133**
New Mexico	8	10	12	12	12	12	12	12	12	12	12	**123**
New York	12	12	12	12	12	12	12	12	12	12	12	**133**
North Carolina	8	0	3	12	12	12	12	12	12	12	12	**107**
North Dakota	0	0	0	0	0	0	0	6	12	12	12	**36**
Ohio	11	12	12	12	12	12	12	12	12	12	12	**127**
Oklahoma	7	12	12	12	12	12	12	12	12	12	12	**121**
Oregon	9	12	12	12	12	12	12	12	12	12	12	**123**
Pennsylvania	11	12	12	12	12	12	12	12	12	12	12	**125**
Rhode Island	9	10	11	12	12	12	12	12	12	12	12	**120**
South Carolina	11	12	12	12	12	12	12	12	12	12	12	**128**
South Dakota	4	4	8	12	12	12	12	12	12	12	12	**107**
Tennessee	8	0	0	1	0	12	12	12	12	12	12	**76**
Texas	12	12	12	12	12	12	12	12	12	12	12	**130**
Utah	9	11	11	12	12	12	12	12	12	12	12	**125**
Vermont	2	5	7	11	12	10	12	12	12	12	12	**102**
Virginia	12	12	12	12	12	12	12	12	12	12	12	**132**
Washington	10	12	12	12	12	12	12	12	12	12	12	**128**
West Virginia	2	9	12	12	12	12	12	12	7	2	12	**98**
Wisconsin	10	12	12	12	12	12	12	12	12	12	12	**129**
Wyoming	0	10	11	10	12	12	12	12	12	12	12	**111**
Total	**412**	**465**	**483**	**515**	**520**	**544**	**552**	**568**	**594**	**590**	**300**	**5,686**

Table 5.3 provides a breakdown of the distribution of loans in the sample database by year. The table indicates that a very small share of loans was issued between 2008 and 2011 with less than 1% of loans each year. Loan distribution is concentrated in the last four years (2014–2018) of the sample. As P2P lending became more popular loan numbers increased, and LendingClub issued more than 400,000 loans each year after 2015. The highest number of loans were issued in 2018, while the lowest amount was seen in 2008. This shows a clear upward trend in the sample in terms of the volume of issued loans. In fact, the loan volumes constantly increased during the period under consideration. On the other hand, between 2015 and 2018, LendingClub's loan growth rates relatively stabilised following the market trends as explored in section 2.4.

To gain further insight into loan composition, in Table 5.4, this study reports the distribution of loans across states. The largest number of loans issued fall into the share of big US states, namely California (14.12%), New York (8.17%) and Texas (8.64%). The share of other states in total issued loans is low, ranging from 3.37 thousand loans issued in North Dakota up to 157 thousand loans issued in Florida. The matter of overwhelming representation of three large states in the sample is duly considered in robustness tests section of this chapter.

Table 5.3: Loan volume and number of loans by year

	Loan volume		Number of loans	
Year	**US$ millions**	**%**		**%**
2008	20.00	0.06%	2393	0.11%
2009	51.80	0.16%	5281	0.24%
2010	126.00	0.39%	12537	0.57%
2011	257.00	0.79%	21721	0.98%
2012	718.00	2.20%	53367	2.41%
2013	1980.00	6.06%	134814	6.09%
2014	3500.00	10.70%	235629	10.65%
2015	6420.00	19.63%	421095	19.03%
2016	6400.00	19.57%	434407	19.63%
2017	6570.00	20.09%	442790	20.01%
2018	6654.00	20.35%	448754	20.28%
Total	**32696.8000**	**100.00%**	**2212788**	**100.00%**

Table 5.4: Distribution of loan volume and number of loans by state

	Loan volume		Number of loans	
	US$ millions	%	thousands	%
Alabama	356.0000	1.19%	26.9817	1.22%
Alaska	81.7000	0.27%	5.2391	0.24%
Arizona	682.0000	2.28%	52.4181	2.37%
Arkansas	211.0000	0.71%	16.6737	0.75%
California	4220.0000	14.12%	308.3431	13.93%
Colorado	637.0000	2.13%	46.9482	2.12%
Connecticut	479.0000	1.60%	34.9281	1.58%
Delaware	83.8000	0.28%	6.2641	0.28%
District of Columbia	75.5000	0.25%	5.3318	0.24%
Florida	2030.0000	6.79%	157.2511	7.11%
Georgia	998.0000	3.34%	72.6409	3.28%
Hawaii	149.0000	0.50%	10.5146	0.48%
Idaho	48.3000	0.16%	3.7103	0.17%
Illinois	1240.0000	4.15%	89.3246	4.04%
Indiana	485.0000	1.62%	36.7849	1.66%
Iowa	0.1128	0.00%	0.0155	0.00%
Kansas	250.0000	0.84%	18.7923	0.85%
Kentucky	275.0000	0.92%	21.3605	0.97%
Louisiana	340.0000	1.14%	25.5093	1.15%
Maine	60.5000	0.20%	4.5907	0.21%
Maryland	749.0000	2.51%	52.7131	2.38%
Massachusetts	717.0000	2.40%	50.8408	2.30%
Michigan	743.0000	2.49%	57.7036	2.61%
Minnesota	512.0000	1.71%	39.0714	1.77%
Mississippi	162.0000	0.54%	12.2256	0.55%
Missouri	462.0000	1.55%	35.3423	1.60%
Montana	78.0000	0.26%	6.2321	0.28%
Nebraska	91.8000	0.31%	7.2505	0.33%
Nevada	409.0000	1.37%	31.6972	1.43%
New Hampshire	147.0000	0.49%	10.9321	0.49%
New Jersey	1160.0000	3.88%	81.3716	3.68%
New Mexico	158.0000	0.53%	11.7749	0.53%
New York	2440.0000	8.17%	183.2034	8.28%
North Carolina	821.0000	2.75%	61.7199	2.79%
North Dakota	46.5000	0.16%	3.3701	0.15%
Ohio	952.0000	3.19%	73.8438	3.34%

Oklahoma	273.0000	0.91%	20.2515	0.92%
Oregon	331.0000	1.11%	26.1301	1.18%
Pennsylvania	1000.0000	3.35%	75.7326	3.42%
Rhode Island	124.0000	0.42%	9.7502	0.44%
South Carolina	366.0000	1.23%	27.2501	1.23%
South Dakota	56.5000	0.19%	4.4526	0.20%
Tennessee	457.0000	1.53%	34.4995	1.56%
Texas	2580.0000	8.64%	182.3418	8.24%
Utah	200.0000	0.67%	14.7462	0.67%
Vermont	59.9000	0.20%	4.8259	0.22%
Virginia	897.0000	3.00%	62.0888	2.81%
Washington	634.0000	2.12%	46.0944	2.08%
West Virginia	104.0000	0.35%	7.7332	0.35%
Wisconsin	379.0000	1.27%	29.2649	1.32%
Wyoming	65.6000	0.22%	4.7111	0.21%
Total	**32696.8000**	**100.00%**	**2212.7880**	**100.00%**

Figure 5.1 presents the LendingClub P2P lending loan distribution across the US states. The figure indicates a high concentration of loans in states of California, New York, Texas and Florida in light blue colour. Followed by these large states are the loans issued along East and West coast, generally trailing the population of states in these areas. The figure reveals another geographical area of concentration of loans issued by LendingClub. The states of Midwest around Great Lakes have large population areas like Chicago, Indianapolis and Detroit. A large concentration of loans issued is also observed in this area of the USA. Other regional areas of the USA are scarcely populated. Thus, LendingClub did not issue many loans in these scarcely populated states with less than 25 thousand loans each in its portfolio. The impact of population centres is duly represented in the regression analysis with including state-specific individual effects and variable representing the population of states.

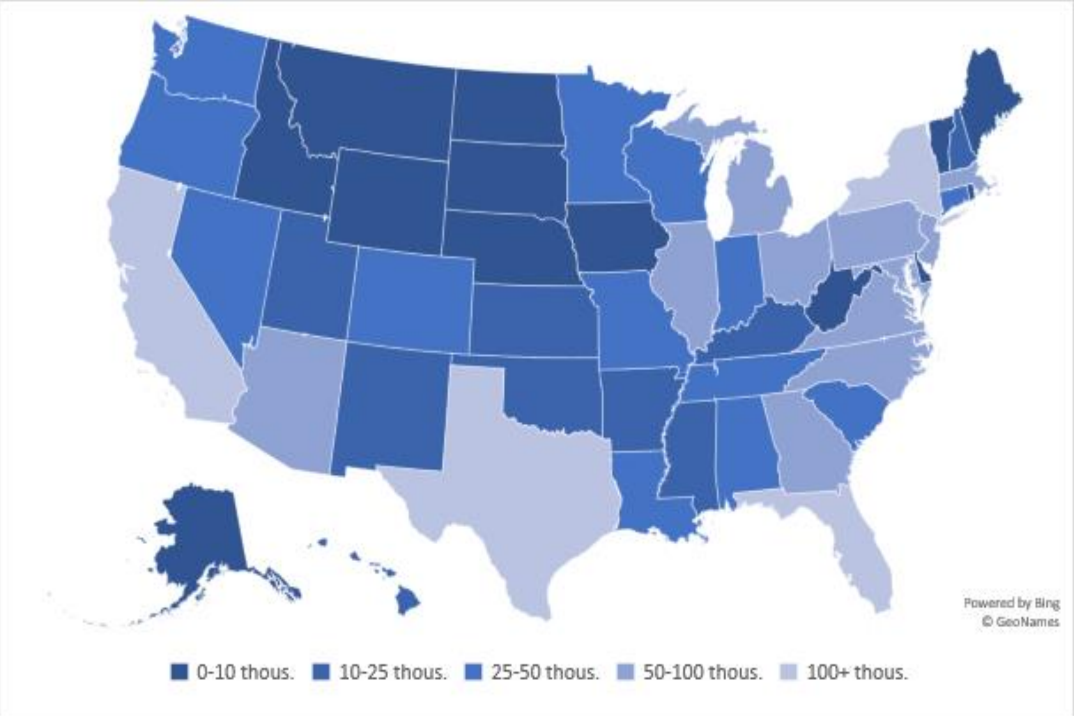

Figure 5.1: Composition of loans issued by LendingClub by US states (2008–2018)

Table 5.5 reports descriptive statistics for the variables used in the main analyses. Mean value of issued monthly loans by LendingClub at each state was US$5.25 million. Of those, US$149.87 thousand on average were classified as bad loans. Mean value for the average interest rate for loans in the sample is 12.92%, which is close to the advertised average interest rate by LendingClub for all loans[13]. Average annual income declared by borrowers oscillates between the lower quartile of US$63,718 to upper quartile of US$77,162. This range generally lower than the USA household mean average income during the 2008–2018 period reported by the US Census Bureau[14]. Average DTI scores for the sample do not exceed the healthy level of leverage recommended by LendingClub with upper quartile at 0.1963 ratio.

[13] LendingClub average interest rate for all terms is 13.00%: <https://www.lendingclub.com/info/demand-and-credit-profile.action>

[14] According to the US Census Bureau, household mean income in the USA ranged between US$68,424 and US$90,021 between 2008 and 2018, respectively.

Table 5.5: Descriptive statistics for variables included in regression analysis

Table 5.5 reports the descriptive statistics for variables included in the regression analysis. The variables include platform-specific, economic, demographic, technological and political characteristics. The variable descriptions are provided in Table 5.1.

Variables	Mean	Median	Std Dev	Lower Quartile	Upper Quartile
Platform-specific					
LOANVOL (US$ thousands)	5253.9960	1333.9130	10500.0000	159.2000	5751.8500
LOANCOUNT (thousands)	352.3167	93.0000	684.7924	15.0000	395.0000
AVEINTRATE	0.1292	0.1295	0.0137	0.1225	0.1379
AVEINCOME	70.2464	70.5092	17.3324	63.7186	77.1628
AVEDTI	0.1715	0.1780	0.0554	0.1440	0.1963
AVEREVOL	0.5183	0.5280	0.1054	0.4739	0.5731
BADLOANSCOUNT (US$ thousands)	9.7099	0.0000	33.1016	0.0000	6.0000
BADLOANSVOL (thousands)	149.8703	0.0000	523.1949	0.0000	81.5250
Economic variables					
MUNI_M	0.0239	0.0257	0.0045	0.0219	0.0267
GDPREAL (US$ millions)	334.8937	224.3030	392.6057	97.5005	417.3320
INFLATION	0.0868	1.0252	0.5877	0.0867	1.3202
NEW_BUS	4817.2600	2805.0000	6681.0720	1341.0000	5571.0000
Demographic, technology and politics					
POPESTIMATE (millions)	6.2123	3.8153	7.5993	1.3302	6.7940
RELIGIOUSITY	0.5446	0.5400	0.1063	0.4800	0.6300
REP	0.4966	0.4962	0.1269	0.4018	0.5728
INTERNETUSERS (thousands)	4018.1420	3526.2220	4106.0960	1661.4570	4263.5290

The author reports a correlation matrix for the dependent, explanatory and control variables in Table 5.6. The table indicates low levels of Pearson’s correlation coefficients for most of the variable pairs with few exceptions. Three variable pairs are of particular concern, and this study resolves this problem with the use of proxy variables. There is a high correlation between the real GDP and loan volumes that was also visible in Table 5.5. The study uses the contribution to percentage change in real GDP (GDP_CONTR) as explained in section 4.6.3. By using GDP_CONTR this study resolves another problem with multicollinearity between NEWBUS and GDP_REAL. This study uses LABOR_FORCE instead of POPEST to resolve the multicollinearity with INTUSE. With these replacements, the correlation matrix does not provide any evidence that the data set suffers from serious multicollinearity issues.

Table 5.6: Correlation matrix

Table 5.6 reports Pearson's correlation coefficients between the variables employed in regression analyses of this chapter. Significant correlations in bold. See Table 5.1 for variable definitions.

	LOANVOL	LOAN COUNT	AVE INTRATE	AVE INCOME	AVEDTI	AVE REVOL	BAD LOANS	MUNI_M	INFLATION
LOANVOL	1								
LOANCOUNT	**0.9979**	1							
AVEINTRATE	-0.1246	-0.1127	1						
AVEINCOME	0.3479	0.3384	-0.0757	1					
AVEDTI	0.0272	0.0275	-0.0141	-0.004	1				
AVEREVOL	-0.3726	-0.3834	0.3413	-0.2976	-0.0764	1			
BADLOANSCOUNT	**0.6262**	**0.6389**	-0.0154	0.2408	0.015	-0.2867			
BADLOANSVOL	**0.6268**	**0.6387**	-0.0154	0.2457	0.0139	-0.2838	1		
MUNI_M	-0.0662	-0.0677	0.1864	-0.4352	-0.2231	0.0930	-0.2772	1	
INFLATION	0.3079	0.3100	-0.0555	0.2082	-0.0511	-0.1194	0.1919	-0.0331	1
GDPREAL	**0.7085**	**0.7174**	-0.0436	0.2112	-0.0945	-0.1547	0.505	0.0158	0.3825
NEW_BUS	0.2627	0.2737	-0.0588	0.1617	-0.0830	-0.1298	0.4907	0.0136	0.3699
POPESTIMATE	-0.0485	-0.0486	-0.0266	-0.0120	-0.0417	-0.0757	-0.0204	-0.0084	0.0268
RELIGIOUSITY	-0.0199	-0.0182	-0.0359	0.1181	-0.0784	-0.0829	-0.025	-0.0108	-0.0392
REPUBLICAN	-0.0059	-0.0031	-0.0114	-0.0329	-0.0403	-0.0176	-0.0132	0.0818	0.2224
INTERNETUSER	-0.0561	-0.0571	-0.0199	-0.0490	-0.0360	0.0142	-0.0344	0.0890	0.0231

Table 5.6: Correlation matrix (Contd.)

	GDPREAL	NEW_BUS	POPESTIM	RELIGIOUSITY	REP
LOANVOL					
LOANCOUNT					
AVEINTRATE					
AVEINCOME					
AVEDTI					
AVEREVOL					
BADLOANSCOUNT					
BADLOANSVOL					
MUNI_M					
INFLATION					
GDPREAL	1				
NEW_BUS	**0.9343**	1			
POPESTIMATE	-0.0709	-0.0863	1		
RELIGIOUSITY	-0.0252	-0.0665	0.0506	1	
REPUBLICAN	0.0150	0.0534	0.1746	-0.4825	1
INTERNETUSER	-0.0484	-0.0616	**0.7842**	0.0179	0.1236

Figure 5.2 depicts the yearly loan portfolio of LendingClub from 2008 to 2018 with the percentage share of overdue loans. From 2008 to 2015 loan portfolio of LendingClub increased dramatically. There is also a slight upward trend in the share of overdue loans (charged off and late loans) between 2010 and 2015. As depicted in Figure 5.2, the volume of loans generally stabilised after 2015 with a drop in overdue loans between 2016 and 2018. As LendingClub issues loans with a maturity of 36 and 60 months, numbers for 2008 do not represent the actual realised delinquencies by LendingClub. In fact, LendingClub goes through a 9-month loan recovery cycle for each overdue loan. Generally, the loan recovery rate is 89% throughout the nine months after the non-payment by the borrower. Considering these aspects of the loan servicing process, this study does not cover the period beyond 2018.

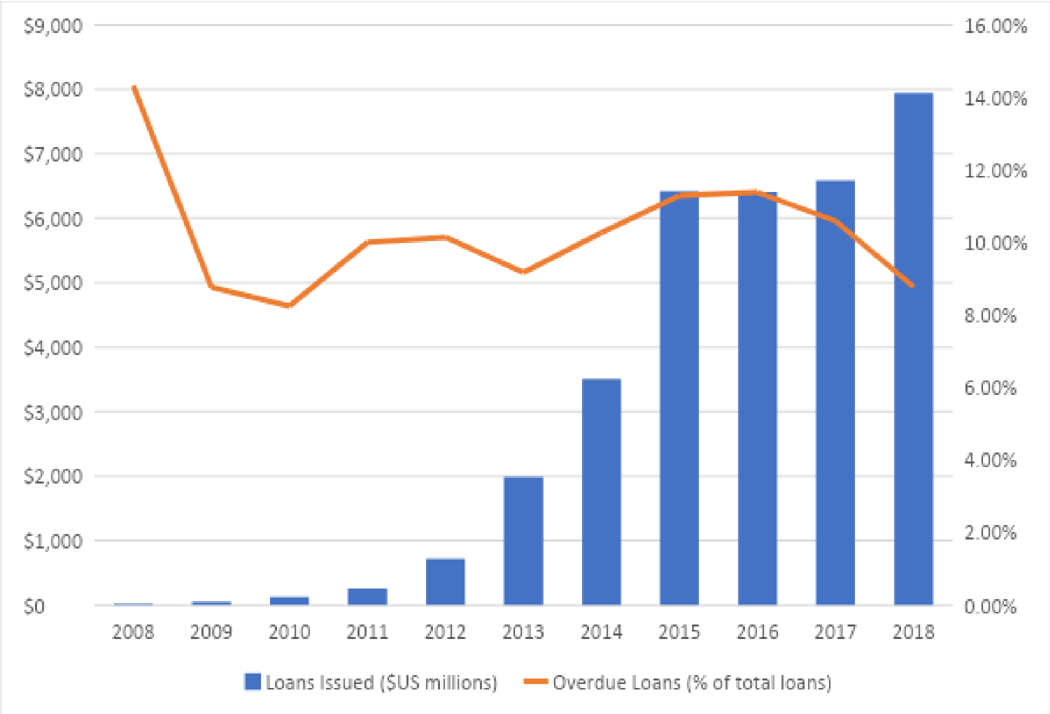

Figure 5.2. Loan portfolio and overdue loans issued by LendingClub (2008–2018)

Source: LendingClub (2020)

Figure 5.3 depicts monthly levels of the probability of default experienced by each state against average interest rate and inflation. The line of linear fitted values with 95% confidence interval is superimposed on the scatter plot. It is observed in Figure 5.3 that the probability of default increases with the rise of average interest rate, when not controlled for any covariates. The reader cannot observe the clear relationship between inflation and probability of default, as the linear fitting line is flat. Scatter plot in Figure 5.3 also indicates the high variability of the observations for the probability of default across the states and time period under consideration. This study resolves this problem by including time and state-specific covariates in regression analysis. The scatter plot also reveals that a substantial number of observations for the probability of default are equal or close to zero. This is the result of a low number of loans issued at certain periods in individual states. This study employs the bootstrap sampling in regression analysis for avoiding overrepresentation of the 'low loan' states in the sample. To more formally test the two hypotheses derived in section 3.5, this study estimates how default probabilities change as a result of average interest rate and inflation holding platform and state-specific characteristics constant.

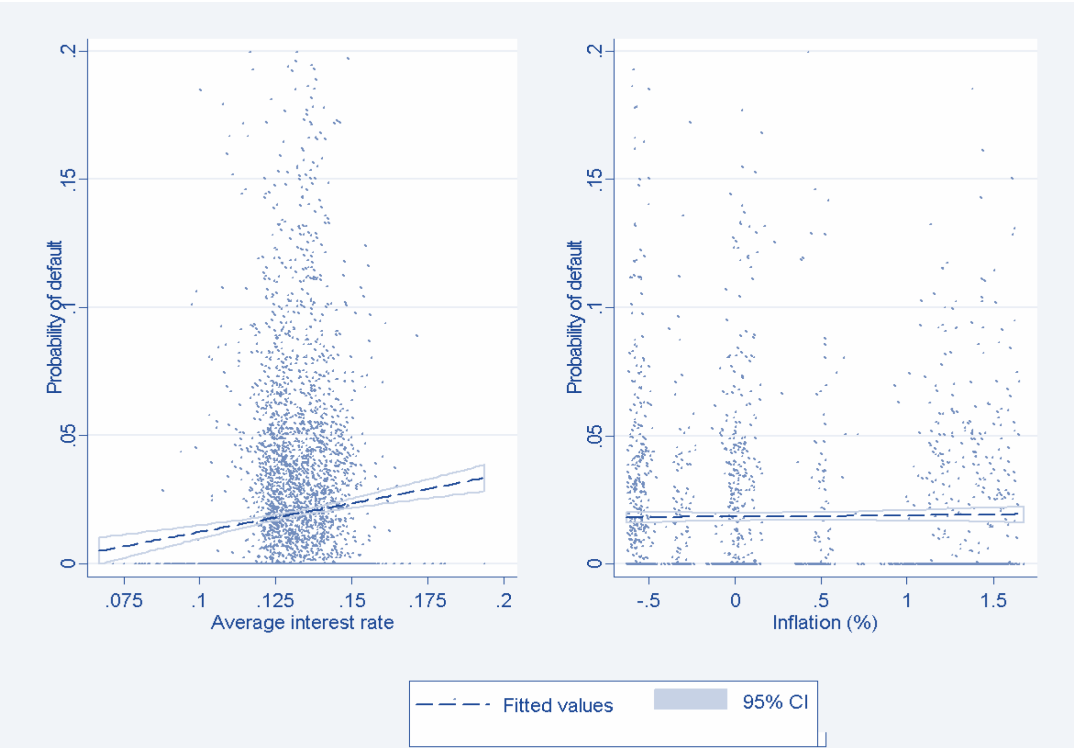

Figure 5.3: Probability of default versus average interest rate and inflation

5.4 Results of baseline regression analysis

Estimation results for baseline regression involving bad debts (PD as in equation [11]) as the dependent variable are reported in Table 5.7 and Table 5.8. Results are based on Fixed Effects Estimation with the constant, year and individual effects. Respective independent variables are lagged according to the model described in section 4.6.3 Sampling size varies from 2855 to 3223 across the models because of missing values and random bootstrapping (100 iterations). Random bootstrap samples allow to safely conclude that the observed variations in variables are not attributed to outliers or missing observations. As it is elaborated in section 4.6.3 of this thesis, both Fixed Effects and Random Effects models estimated in this Chapter. Then based on the results of the Hausman specification test, this study decides which model results should be reported. Hausman specification test reported significant Chi-square statistics[15] indicating that the Fixed Effects estimation method is preferred[16].

The fit of the models in Table 5.7 based on overall R-square ranges from 0.4379 to 0.4720. These values indicate that independent variables collectively explain around 43%-47% of changes in the dependent variable. The main variables of interest are the average interest rate and inflation. Models (1-4) in Table 5.7 depict the dependent variable (PD) as a function of the average interest rate (AVEINTRATE) and control variables. Average interest rate is significantly positive across all 4 models in Table 5.7. Variable coefficients vary from 0.5042 to 0.6064. Average interest rate is significantly positive across all 4 models in Table 5.7. Variable coefficients vary from 0.5042 to 0.6064 with different combinations of control variables. This finding indicates that interest rates significantly and positively affect delinquency rates represented by the probability of default (PD).

[15] Reported in Table 5.7 and 5.8

[16] Results from Fixed Effects estimation are reported in Appendix B.

Table 5.7: Average interest rate and the likelihood of loan default

Table 5.7 reports the results for the Fixed Effects panel data estimation representing the effect of platform-specific variable (average interest rate) on the probability of default with control variables. Estimations are based on equation [8]. Estimation model employs the proportion of bad loans to total loans (PD) as the dependent variable. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

	Model 1	Model 2	Model 3	Model 4
Variables	**DV= PD**	**DV= PD**	**DV= PD**	**DV= PD**
AVEINTRATE	0.5042	0.5207	0.5588	0.6064
	(0.3584)	(0.3626)	(0.3905)	(0.3926)
LOANVOLUME	0.2970***	0.3096***	0.2994***	0.2852***
	(0.0322)	(0.0330)	(0.0354)	(0.0374)
AVEDTI	0.7292***	0.7530***	0.8354***	0.8188***
	(0.2157)	(0.2181)	(0.2322)	(0.2326)
INTUSERS	0.1049***	0.0896***	0.0897***	0.0892***
	(0.0080)	(0.0086)	(0.0089)	(0.0089)
GDP_CONT	-0.1200***	-0.1273***	-0.1400***	-0.1434***
	(0.0388)	(0.0395)	(0.0421)	(0.0422)
AVEINCOME	0.0579	0.0423	0.0419	0.0497
	(0.2678)	(0.2703)	(0.2892)	(0.2892)
NEW_BUS		0.3097***	0.3059***	0.3138***
		(0.0430)	(0.0467)	(0.0467)
REPUBLICAN			-0.0242	0.0112
			(0.1491)	(0.1522)
LABOR_FORCE				2.2457
				(1.9325)
Constant, Yr. & Ind. Effects	Yes	Yes	Yes	Yes
Overall R-squared	0.4534	0.4379	0.4382	0.4720
N	3223	3121	3121	2855
Hausman's specification test: chi-square statistic for Random Effects versus Fixed Effects Models				
				168.81* **

Table 5.8 reports the results of estimating the coefficients based on equation [9] with the inflation rate as an explanatory variable. In Models (1-4) of Table 5.8, the author uses the same set of control variables as in Table 5.7. Inflation rate (INFLATION) is the monthly measure of the change in seasonally adjusted consumer price index for respective US states. The results of Model (1) indicate that the coefficient for inflation is significant and positive (0.4364). The coefficients for INFLATION are robust when the author includes the NEW_BUS, REPUB and LABOR_FORCE, as control variables (Models (2), (3) and (4) respectively). The coefficients for these variables are positive and significant across different models. Coefficients for INFLATION are significantly positive varying from 0.4445 to 0.4556.

Control variables are also important for considering. Loan volume has significant positive coefficients across all four models. The coefficient for loan volume varies between 0.2853 to 0.3096 across the reported four models in Table 5.7. Based on Model 4 (Table 5.7), which makes the baseline regression in further analysis, a 1% increase in loan volumes leads to a 0.28% increase in default probability. This coefficient value is significantly different from zero under 0.01 significance level as per the t-test. Internet users and average DTI score have positive and significant coefficients across all models in the first group of models (Table 5.7). While NEW_BUS is significantly positive, indicating that a 1% rise in new businesses created leads to around 0.31% increase in bad to all loans ratio.

Table 5.8: Inflation and the likelihood of loan default

Table 5.8 reports the results for the Fixed Effects panel data estimation representing the effect of platform-specific variable (average interest rate) on the probability of default with control variables. Estimations are based on equation [9]. Estimation model employs the proportion of bad loans to total loans (PD) as the dependent variable. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

	Model 1	**Model 2**	**Model 3**	**Model 4**
Variables	**DV= PD**	**DV= PD**	**DV= PD**	**DV= PD**
INFLATION	0.4364***	0.4356***	0.4445***	0.4556***
	(0.1241)	(0.1243)	(0.1242)	(0.1243)
LOANVOLUME	0.6596***	0.6588***	0.6521***	0.6287***
	(0.0366)	(0.0371)	(0.0372)	(0.0393)
AVEDTI	0.5386**	0.5384**	0.5400**	0.5152**
	(0.2136)	(0.2137)	(0.2133)	(0.2135)
INTUSERS	0.0106	0.0107	0.0124*	0.0113*
	(0.0065)	(0.0065)	(0.0066)	(0.0066)
GDP_CONT	-0.0950***	-0.0951***	-0.0928***	-0.0953***
	(0.0341)	(0.0341)	(0.0341)	(0.0341)
AVEINCOME	0.7889**	0.7909**	0.7653**	0.7322**
	(0.3458)	(0.3463)	(0.3461)	(0.3462)
NEW_BUS		0.3770***	0.3679***	0.3624***
		(0.3684)	(0.0684)	(0.0681)
REPUBLICAN			0.3119***	0.3471***
			(0.1165)	(0.1180)
LABOR_FORCE				3.2428*
				(1.7799)
Constant, Yr. & Ind. effects	Yes	Yes	Yes	Yes
Overall R-squared	0.3675	0.3668	0.3516	0.3410
N	3227	3124	3124	2858
Hausman's specification test: chi-square statistic for Random Effects versus Fixed Effects Models				
				399.80 ***

Additional analysis of control variables shows several relationships that might have significant practical implications. In terms of control variables representing the macroeconomic environment and business sentiment, baseline regression revealed a couple of important implications. This study shows that GDP growth has a negative and significant impact on borrower delinquencies. Increase in GDP growth reduces the probability of default among P2P loans. This was true for baseline regression models via variable GDP_CONTR, as presented in Table 5.7 and Table 5.8. Another variable which is related to economic development, namely NEW_BUS, has significant positive coefficients throughout baseline regression results. NEW_BUS is significantly positive, indicating that a 1% rise in created new businesses leads to around 0.30% increase in bad to all loans ratio (PD). This may be because of the specific character of P2P lending industry that reflects more on new and small businesses, rather than overall business sentiment.

5.5 Results of instrumental variable estimation

The impact of average interest rate and inflation on bad loans was also analysed via two-stage GMM Regression with instrumental variables. Table 5.9 presents the two-stage GMM regression results with instrumental variables of average interest rate and inflation. State-level unemployment rate and earnings were taken as instrumental variables for average interest rates. Interest rate yielded a significant positive coefficient with these instrumental variables. The municipality and Federal Reserve rates were used as instrumental variables for inflation.

Table 5.9 shows that instrumental variables yielded significant coefficients. Average interest rate and inflation retain their significantly positive coefficients. The study tests the overall validity of the instruments by implementing the Sargan specification test, which, under the null hypothesis of valid moment conditions, is asymptotically distributed as chi-square (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). Instrument diagnostic tests also favour the use of two models in Table 5.9 with their respective instrumental variables.

Table 5.9: Impacts of average interest rate and inflation on bad loans (two-stage GMM regression with instrumental variables)

Table 5.9 presents the two-stage GMM regression results with instrumental variables of average interest rate and inflation. All model specifications employ robust standard errors in parentheses (* *p*<0.10, ** p<0.05, *** *p*<0.01)

	Average interest rate and the probability of default		**Inflation and the probability of default**	
	1st Stage	2nd Stage	1st Stage	2nd Stage
	DV= AVEINTRATE	DV= PD	DV= INFLATION	DV= PD
AVEINRATE/INFLATION		5.1242***		1.8528***
		(1.0460)		(0.3028)
UNEM_RATE	-0.0308***			
	(0.0035)			
EARNINGS	-0.0035*			
	(0.0021)			
MUNI_M			0.0099***	
			(0.0032)	
FEDFUNDS			-0.0812***	
			(0.0038)	
LOANVOLUME	-0.0020***	-0.0029	0.0011	-0.0182
	(0.0004)	(0.0121)	(0.0015)	(0.0118)
AVEDTI	-0.0298***	-0.3279**	0.0491***	-0.5399***
	(0.0045)	(0.1555)	(0.0186)	(0.1456)
INTUSERS	0.0006***	0.0001	-0.0010**	0.0037
	(0.0001)	(0.0042)	(0.0005)	(0.0042)
GDP_CONT	0.0000	0.0236	-0.0064**	0.0358*
	(0.0006)	(0.0212)	(0.0027)	(0.0213)
AVEINCOME	0.0015	0.2498	-0.0084	0.2966
	(0.0070)	(0.2272)	(0.0288)	(0.2286)
NEW_BUS	-0.0616***	0.4437**	-0.0012	0.0826
	(0.0049)	(0.1830)	(0.0202)	(0.1599)
REPUBLICAN	-0.0085***	-0.0478	-0.0493***	-0.0065
	(0.0021)	(0.0680)	(0.0086)	(0.0692)

Table 5.9: Impacts of average interest rate and inflation on bad loans (Contd.)

LABOR_FORCE	0.2080***	-1.3321	0.8413***	-0.7522
	(0.0367)	(1.1028)	(0.1550)	(1.1153)
Constant, Yr. & Ind. effects	Yes	Yes	Yes	Yes
R-squared		0.0299		0.0178
N	1000 (Bootstrap sampling)	1000 (Bootstrap sampling)	1000 (Bootstrap sampling)	1000 (Bootstrap sampling)
Instrument diagnostics tests:				
Test of endogeneity: GMM distance test statistic of endogeneity		29.7714***		30.6499***
Underidentification test: (Kleibergen-Paap rk LM statistic)		892.5375***		646.5675***
Weak identification test: (Cragg-Donald Wald F statistic)		486.2367		343.6208
Overidentification test: Sargan (1958) $\chi 2$		1.1396		0.3951
[p-value]		[0.2857]		[0.8760]

5.6 Regression results for subsamples of the data set

The chapter further analyses the subsamples based on the median loan volume. Two subsamples include observations with lower than median and higher than median loan volumes. Table 5.10 provides regression results for two models with respective two sample coefficient tests. The average interest rate tends to significantly affect bad loans in both subsamples. The coefficient for the average interest rate is higher for the second subsample (higher than median loan volumes) compared with the first subsample (lower than the median loan volume). However, two sample coefficient tests indicate that the difference between the coefficients is not significant. The effect of inflation on bad loans behaves similarly. The magnitude of the impact of inflation on bad loans tends to be higher for the second subsample with a bigger coefficient. Whereas, Chow test chi-square statistic is 0.34 and insignificant to state that there is a difference between the coefficients.

Table 5.10: Impact of average interest rate and inflation on the probability of default: aggregate loan volumes

Table 5.10 presents the baseline regression results for two subsamples. Subsamples are based on the criteria of loan volumes in states being higher or lower than the median level. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01)

	Average interest rate and the probability of default		Inflation and the probability of default	
	Panel A: Lower than median loan volume	**Panel B: Higher than median loan volume**	**Panel A: Lower than median loan volume**	**Panel B: Higher than median loan volume**
Variables	DV = PD	DV = PD	DV = PD	DV = PD
AVEINTRATE/INFLATION	0.6981**	0.8374***	0.1022	0.2064***
	(0.3437)	(0.3225)	(0.1714)	(0.0799)
LOANVOLUME	-0.2639***	-0.5066***	-0.0682***	-0.0283**
	(0.0467)	(0.0397)	(0.0214)	(0.0128)
AVEDTI	-0.4039*	-0.3720**	-0.7570***	-1.0807***
	(0.2153)	(0.1705)	(0.2051)	(0.1693)
INTUSERS	-0.0020	-0.0048	-0.0048	-0.0043
	(0.0090)	(0.0043)	(0.0094)	(0.0045)
GDP_CONT	0.1096***	-0.0029	0.1436***	0.0059
	(0.0391)	(0.0231)	(0.0408)	(0.0239)
AVEINCOME	-0.1498	0.9572***	-0.3679*	-0.0222
	(0.2135)	(0.3698)	(0.2188)	(0.3805)
NEW_BUS	0.0334	0.3437**	-0.3298	-0.0317
	(0.3319)	(0.1695)	(0.3408)	(0.1764)
REPUBLICAN	-0.6251***	-0.0709	-0.8527***	-0.2242***
	(0.2204)	(0.0703)	(0.2206)	(0.0720)
LABOR_FORCE	-8.4458***	0.9683	-10.5615***	-5.2083***
	(2.1979)	(1.2931)	(2.2441)	(1.2508)
Constant, Yr. & Ind. effects	Yes	Yes	Yes	Yes
Overall R-squared	0.0824	0.0721	0.0760	0.0836
N	5776	5776	5776	5776
Two sample coefficient test: (Chow test chi-square statistic for Aveinrate/Inflation)		0.11		0.34

The study also analysed the functional form in the context of subsamples based on religiosity level of US states and reported in Table 5.11. The first subsample includes observations with higher than the median religiosity, while the second subsample includes observations with lower than the median level of religiosity. The coefficients for average interest rates are significantly positive for both subsamples. The coefficient for the average interest rate for low religiosity subsample is higher than the high religiosity states. This might indicate that the average interest rate affects bad loans at a higher magnitude in low religious states compared with high religious states. Nevertheless, the two-sample coefficient test proved the difference between these coefficients to be insignificant.

The impact of inflation proved to be significantly different among two subgroups. Inflation coefficient is -0.2079 for high religiosity subgroup and 0.4680 for low religiosity subgroup. Two sample coefficient test for inflation yielded a chi-square statistic of 20.96 that indicates a significant difference in coefficients. Specifically, inflation has a significant negative impact on bad loans among high religious states. On the contrary, the impact is significantly positive among low religious states.

Table 5.11: Impact of interest rate and inflation on the probability of default (for subsamples of high and low religious states)

Table 5.11 presents the baseline regression results for two subsamples. Subsamples are drawn based on the religiosity of states. Median religiosity level is based on the variable of 'Religiosity'. Refer to Table 5.1 for the variable description. All model specifications employ robust standard errors in parentheses (* *p*<0.10, ** *p*<0.05, *** *p*<0.01)

	Average interest rate and the probability of default		**Inflation and the probability of default**	
	Panel A: High religiosity	**Panel B: Low religiosity**	**Panel A: High religiosity**	**Panel B: Low religiosity**
	DV= PD	DV= PD	DV= PD	DV= PD
AVEINRATE/ INFLATION	0.6733**	1.1638***	-0.2079**	0.4680***
	(0.3062)	(0.3847)	(0.0996)	(0.1082)
LOANVOLUME	-0.3579***	-0.5305***	-0.0677***	-0.4840***
	(0.0319)	(0.0405)	(0.0145)	(0.0389)
AVEDTI	-0.6243***	-0.0246	-1.4671***	-0.0996
	(0.1796)	(0.2179)	(0.1632)	(0.2170)
INTERNETUSERS	-0.0130***	0.0202**	-0.0152***	0.0209***
	(0.0043)	(0.0079)	(0.0045)	(0.0079)
GDP_CONTRIB	-0.0311	0.0557*	-0.0125	0.0601**
	(0.0270)	(0.0303)	(0.0279)	(0.0303)
AVEINCOME	0.1902	0.2609	-0.4371*	0.3231
	(0.2530)	(0.3758)	(0.2570)	(0.3756)
NEW_BUS_PROP	0.5070***	-0.3112	0.1666	-0.3504
	(0.1728)	(0.2964)	(0.1796)	(0.2957)
REPUBLICAN	-0.0468	-0.1763	-0.2527	-0.1242*
	(0.0780)	(0.1183)	(0.2206)	(0.0720)
LABOR_FORCE	-1.7698	1.0454	-6.5838***	-0.2583
	(1.4581)	(1.5799)	(1.4248)	(1.5279)
Overall R-squared	0.0686	0.0635	0.0679	0.0565
N	6336	5216	5891	5217
Two sample coefficient test: (Chow test chi-square statistic for Aveinrate/Inflation)		1.23		20.96***

Regression analysis was also conducted in the context of rating. The study divided the sample database into subsamples based on ratings. Loans in each state were aggregated into three subgroups of A&B, C&D and E, F&G rated loans. Then, the proportion of bad loans were calculated for each of the subgroups. Table 5.12 reports result from the analysis for each of the subgroups. The regression model follows the same method as it was in the baseline regression. The average interest rate has a significant positive impact on bad loans across all three subsamples. However, the magnitude of the impact is increasing as the rating of loans deteriorates. A 1% increase in the average interest rate leads to 0.1732% increase in the proportion of bad loans for A&B graded loans. The same change leads to 0.5964 percentage increase in the proportion of bad loans among E, F&G rated loans. Wald test of equality of coefficients confirmed a significant difference between the coefficients. Thus, low graded loans are prone to being more sensitive to changes in interest rate.

The same behaviour can be observed for the relationship between inflation and the proportion of bad loans. Beta coefficients for inflation tend to increase as the rating of loans decrease. However, Wald test of equality of coefficients did not confirm the significant difference between the coefficients.

Table 5.12: Impact of average interest rate and inflation on the probability of default: grading of loans

Table 5.12 presents the baseline regression results for three subsamples. Subsamples are drawn based grading of loans. Refer to Table 5.1 for variable description. All model specifications employ robust standard errors in parentheses (* *p*<0.10, ** *p*<0.05, *** *p*<0.01)

	Average interest rate and the probability of default			**Inflation and the probability of default**		
	A & B Grade	**C & D Grade**	**E, F & E Grade**	**A & B Grade**	**C & D Grade**	**E, F & E Grade**
	DV=PD	DV=PD	DV=PD	DV=PD	DV=PD	DV=PD
AVEINRATE/INFLATION	0.1732**	0.4697***	0.5964***	0.1957	0.2362**	0.3892***
	(0.0348)	(0.0834)	(0.0861)	(0.1250)	(0.1105)	(0.1017)
LOANVOLUME	0.7816***	0.8461***	0.7694***	0.7829***	0.6016***	0.5858***
	(0.0860)	(0.0495)	(0.0763)	(0.1372)	(0.1599)	(0.1076)
AVEDTI	0.3500***	0.7868***	0.3750***	0.3537***	0.7846***	0.1808***
	(0.1140)	(0.0918)	(0.0842)	(0.0972)	(0.0915)	(0.0368)
INTERNETUSERS	0.0224***	0.0326***	0.0141*	0.0227***	0.0326***	0.0208***
	(0.0066)	(0.0088)	(0.0073)	(0.0065)	(0.0083)	(0.0067)
GDP_CONTRIB	-0.0095	-0.0481*	-0.0475**	-0.0185	-0.0623**	-0.0702**
	(0.0278)	(0.0285)	(0.0212)	(0.0319)	(0.0294)	(0.0313)
AVEINCOME	0.3839	0.2333	0.0444***	0.0667	0.3448	0.7758***
	(0.5962)	(0.4131)	(0.0137)	(0.1377)	(0.3712)	(0.0955)
NEW_BUS_PROP	0.2396	0.6719**	0.1416	0.3164	0.7733**	0.2767
	(0.2395)	(0.3206)	(0.1749)	(0.1989)	(0.3226)	(0.1941)
REPUBLICAN	0.3591**	0.4534***	0.1046	0.3511**	0.4569***	0.1252
	(0.1452)	(0.1103)	(0.1041)	(0.1421)	(0.0953)	(0.1129)
LABOR_FORCE	0.1403	0.2107	0.1889	0.1384	0.2101	0.2403
	(0.1619)	(0.2228)	(0.1905)	(0.1663)	(0.2455)	(0.1818)
Overall R-squared	0.0420	0.0386	0.0482	0.0416	0.0379	0.0383
N	1307	1736	761	1307	1736	761
Wald test of equality of coefficients: (Chow test chi-square statistic for Aveinrate/Inflation)			21.78***			1.58

5.7 Robustness tests

As the last step in the analysis of this chapter, this study performs robustness tests by excluding certain observations from the sample and report in Table 5.13. In the first subsample, this study excludes observations with a high level of debt. This study based these observations on revolving utilisation rates that measure debt as a proportion of income. Sample 1 in Table 5.13 exclude observations with high average revolving utilisation rates (higher than 0.5). A regression method for this subsample follows the same model and control variables as for the baseline regression.

The author also noticed the fact that the sample periods roughly cover two different periods in terms of market interest rate conditions. Following the world financial crisis, the Federal Reserve Bank of the United States kept baseline interest rates near zero for a prolonged period of time. As a result of this policy, the sample contains observations for periods with high-interest rates compared with the majority of observations. Therefore, a separate subsample was drawn that exclude high-interest period. Sample 2 in Table 5.13 reports the results for this subsample. The sample excludes periods with Federal Reserve target interest rate higher than 100 basis points.

Sample 3 in Table 5.13 reports the results for the subsamples that exclude three large states in terms of real GDP. These states are California, Texas and New York, which are large in terms of their real GDP and accordingly, higher loan volumes and defaults. Therefore, the inclusion of these states in earlier models could have distorted regression results.

All three samples reported in Table 5.13 indicate that beta coefficients for interest rate are consistent with baseline regression. Interest rate tends to have a significant positive impact on the probability of default. However, this study observed some inconsistencies in beta coefficients for inflation. Specifically, Sample 1 underestimates the impact of interest rate on bad loans, while sample 3 overestimates it. The results from the Sample 2 report an insignificant coefficient for the interest rate.

Table 5.13: Impact of inflation and average interest rate on the probability of default: robustness tests

Table 5.13 presents the baseline regression results for three subsamples. Subsamples are formed by excluding several categories of observations. Sample 1 reports the results for the subsamples that exclude observations with high average revolving utilisation rates (higher than 0.5). Sample 2 reports the results for the subsamples that exclude high-interest periods (periods with Federal Reserve target interest rate higher than 100 basis points). Sample 3 reports the results for the subsamples that exclude three large states in terms of real GDP (California, Texas and New York). All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01)

Sample 1. Excluding observations with high average revolving utilisation rates		
Variables	**DV = PD**	**DV = PD**
AVEINRATE	0.9578***	
	(0.2543)	
INFLATION		0.1299*
		(0.0708)
Controls	Yes	Yes
Constant, Yr. & Ind. effects	Yes	Yes
Overall R-squared	0.0385	0.0239
N	1192	1195
Sample 2. Excluding observations with high-interest rate		
Variables	**DV = PD**	**DV = PD**
AVEINRATE	0.9585***	
	(0.2333)	
INFLATION		-0.0408
		(0.0807)
Controls	Yes	Yes
Constant, Yr. & Ind. effects	Yes	Yes
Overall R-squared	0.0123	0.0126
N	1252	1252
Sample 3. Excluding observations for three large states		
Variables	**DV = PD**	**DV = PD**
INFLATION	0.9695***	
	(0.2485)	
AVEINRATE		0.2701***
		(0.0748)
Controls	Yes	Yes
Constant, Yr. & Ind. effects	Yes	Yes
Overall R-squared	0.0378	0.0281
N	1174	1174

5.8 Discussion and concluding remarks

This study tested the effect of various determinants on P2P loan delinquencies in a cross-state study setting. As it has been indicated in the literature review section of this thesis, existing literature largely lacks empirical studies on the selected topic. Therefore, it is extremely difficult to compare the findings with earlier studies and conclusions might be limited in their generalisation. This and other relevant limitations of this study are duly considered in the last part of this section. This section largely relies on literature that is available and structured according to the main hypotheses of the study highlighted earlier in this chapter. Since the author found no studies related to the current study in P2P lending market, this study largely relies on studies in traditional financial markets.

This chapter provides the first evidence on the implications of interest rate on delinquencies in P2P lending market. Using the average interest rate as the main measure of market interest rate, as predicted, this study finds that interest rates significantly and positively affect delinquency rates represented by the probability of default. Specifically, higher interest rates for loans link to higher delinquency rates, causing more borrowers to default or miss payments on their outstanding loans. Results of this chapter hold even after controlling for endogeneity and robustness tests. This result falls in line with the only available study (Serrano-Cinca et al., 2015) exploring the relationship between the interest rate and defaults in P2P lending. The significant positive relationship is also consistent with the empirical studies in traditional financial markets that concluded that surge in interest rate increases loan defaults and hence nonperforming loans (Espinoza and Prasad, 2010; Beck et al., 2000). However, the findings of this study contradict with the studies of Jakubık (2006), Goel and Hasan (2011), and Ghosh (2015) that indicated a negative or insignificant relationship between interest rates and defaults.

Further analysis shows that the positive relationship between the interest rate and delinquencies is more pronounced as loan grades fall. It is supported with two earlier studies of Serrano-Cinca et al. (2015), and Wei and Lin (2016) that indicated the importance of grading for estimating P2P loan defaults. However, Serrano-Cinca et al. (2015) and Wei and Lin (2016) only provide the direct impact of grading on defaults. This study provides the first evidence in terms of the sensitivity of interest rates in determining delinquencies within each grading category.

This chapter also briefly considered the impact of interest rate on the probability of default within the context of subsamples based on loan volumes. This interaction in the context of loan volumes explored the impact of high loan volumes on social welfare costs for borrowers (represented in higher interest rates). Therefore, this study expanded on the findings of existing literature by Wei and Lin (2016) who explored the social welfare costs of P2P lending. This chapter did not find significant differences between the subsamples in terms of the interaction between interest rates and defaults. As this aspect of the thesis is out of the research scope the author does not go into further analysis of this issue. Rather, this aspect is duly mentioned in the last chapter of this thesis as a prospective area for further research.

This study is unique in terms of exploring the impact of inflation rate on delinquencies in P2P lending market. This issue has been prevalent in traditional financial literature, though there was no known study in P2P lending market. Inflation was found to have a significant positive coefficient in the baseline model and remained to be so in the model with instrumental variables. This result is consistent with empirical evidence in existing studies of commercial banks (Klein, 2013; Skarica, 2014; Ghosh, 2015).

On the other hand, the coefficient for inflation rate was unstable throughout robustness tests. Specifically, this chapter found that the inflation coefficient was insignificant and negative in the sample that excludes high-interest periods. The variable of inflation rate had an insignificant coefficient in Sample 2 of robustness tests in Table 5.13. This proves, to a certain degree, that this variable does not influence P2P lending volume in high-interest periods. This finding contradicts with earlier findings of Wongbangpo and Sharma (2002) and Larrain (2010) that proved a negative relationship between inflation and lending volume. Thus, the findings of this chapter only partially prove the second hypothesis and partly contradict with earlier findings. This necessitates further analysis with a larger database and more advanced analysis that are highlighted in the last section of this chapter.

The additional analysis of control variables shows several relationships that might have significant practical implications. In terms of control variables representing the macroeconomic environment and business sentiment, baseline regression revealed a couple of important implications. Existing studies of Siam, Khrawish and Jaradat (2010); Mollick (2014) proved the positive impact of economic development on alternative financial markets. This study showed that GDP growth has a positive but insignificant impact on borrower delinquencies. This was true for two baseline regression models via variable GDP_CONTR as presented in Table 5.7 and Table 5.8, contradicting strong evidence from traditional financial markets (Beck et al., 2000; Skarica, 2014; Jakubik and Reininger, 2013). However, another variable which is related to economic development, namely NEWBUS, has significant positive coefficients throughout baseline regression results. This may be because of the specific character of P2P lending industry that reflects more on new and small businesses, rather than overall business sentiment. These aspects of the findings are duly highlighted in the last chapter of this thesis and further analysed in the next chapter (Chapter 6) of this thesis.

Prior literature linked religious adherence to lower risk-taking and lower involvement in questionable activities (Hilary & Hui, 2009; Dyreng, Mayew, & Williams, 2012; Callen & Fang, 2015). Existing literature also indicated significant differences in loan terms and financial reporting based on religiosity (McGuire, Omer, & Sharp, 2011; He & Hu, 2016). This study was unique in terms of providing evidence that inflation has a significantly different relationship with delinquency rates based on the degree of religiosity. This is to be further explored in the next chapters, which would provide additional insights into the aspect of religiosity in P2P lending market.

5.9 Generality of findings

This study is one of the first empirical investigations of P2P lending markets. In this chapter, unlike earlier studies, the author relied on the extended data set over 10 years. This chapter aimed to reveal the impact of economic variables on P2P lending delinquencies utilising panel data regression analysis. This empirical chapter investigated multiple factors related to the default risks of online P2P platforms based on LendingClub loan-book data. Many of the findings are supported by the literature on banks and traditional financial services. This study is the first to shed light on the online P2P lending literature by extending the understanding of the probability of default via ‘bad loans’.

The main analysis in this chapter was based on the sample database from LendingClub covering the time period from 2008 to 2018. The findings nonetheless should still be relevant up until 2020 and beyond, as well to other P2P lending platforms in the USA. First, the model framework was derived from well-proven traditional financial markets, with relative forces affecting delinquencies being highly analogous. Second, LendingClub is very similar to most of its rival platforms, including their market niche, loan request process and risk assessment. Third, the incentives of all major stakeholders (platform, borrower, and lender) are consistent with most, if not all, P2P lending platforms that the author is aware of. Nonetheless, the generalisation of findings may not apply to other countries beyond the USA, mainly due to different regulatory frameworks. This study explores the P2P lending market in European markets in Chapter 6, after which the solid conclusions are made on similarities and differences between these regions.

Chapter 6:

Determinants of Loan Defaults in European P2P Lending Market

6.1 Outline of the chapter

This chapter provides a detailed description of the result and interpretation of the research work based on the analysis of Bondora (Estonia) and Mintos (Latvia), two of the leading P2P lending platforms in Continental Europe. Both platforms operate across the multiple countries of the European Union that make them ideal for exploring the credit risk incurred by P2P lending platforms in Europe. The first part of this chapter consists of a descriptive analysis of the data set compiled by the author. Descriptive analysis is followed by statistical tests and regression analysis.

6.2 Descriptive statistics

This chapter uses the aggregated loan-book database from Bondora and Mintos. The scope of this chapter covers the loans issued across the multiple countries of the European Union (EU). Bondora issues loans in Finland, Estonia and Spain. Bondora investors are scattered among 88 countries, including all countries of EU and accredited investors from outside the European Union (EU). Bondora falls into the category of direct P2P lending platform, as explained in Chapter 2 (section 2.3). Bondora online platform directly connects investors with borrowers via its website. Mintos falls into P2P marketplace category that does not create its own P2P lending platform. The marketplace platform of the company simultaneously lists loans from multiple lending companies, the so-called 'loan originators'. Loan originators listed in Mintos are based in 30 countries, including ten countries of the European Union (EU). Investors in the marketplace are from 66 countries, although Mintos does not disclose information about the investor categories and origination. The combined database consists of monthly observations for each country and timespan of ranges from January 2015 to December 2019. Countries included in the database are Czech Republic, Denmark, Estonia, Finland, Latvia, Lithuania, Poland, Spain, Sweden and the United Kingdom. The database used in this empirical chapter is balanced panel data and contains all the observations for the analysed period. Variables used in this chapter include a wider range of borrower and country-specific information. Table 6.1 provides the list and description of the variables used in this chapter.

Table 6.1: Description of variables used in Chapter 6 analysis

Variable	Description of variable	Source
Dependent variables		
PD	Probability of default as in equation [11]. Share of bad loans in total loans in councry *i* at time *t*. (monthly)	*Bondora, Mintos*
Explanatory variables		
AVEINTRATE	Average interest rate on loans issued by Bondora and Mintos in country *i* at time *t* as per equation [12] (monthly, percentage points)	*Bondora, Mintos*
INFLATION	Monthly change in seasonally adjusted consumer price index for all goods by country as per equation [13] (percentage points)	*OECD (2020), Inflation (CPI) (indicator). doi: 10.1787/eee82e6e-en (Accessed on 13 June 2020)*
Independent variables, $\boldsymbol{X^{Platform}}$- platform-specific		
LOANVOLUME	Total volume of outstanding loans issued in country *i* at time *t* (monthly, in euros [€]). Log differenced values as in equation [14]	*Bondora, Mintos*
AVEDTI	Average DTI score of borrowers in country *i* at time *t*.	*Bondora, Mintos*
AVEINCOME	Average annual income of borrowers in country *i* at time *t* (monthly, in euros [€]). Log values.	*Bondora, Mintos*
AVEAMOUNT	Average value of individual loans issued in country *i* at time *t* (monthly, in euros [€]). Log values.	*Bondora, Mintos*
AVEDURATION	Average loan duration of loans in country *i* at time *t*.	*Bondora, Mintos*
AVERATING	Average rating of loans in country *i* at time *t*. Ratings transferred into coded continues variable.	*Bondora, Mintos*
AVEAGE	Average age of borrowers when signing the loan application in country *i* at time *t*	*Bondora, Mintos*
Independent variables, $\mathbf{X}^{\boldsymbol{Macro}}$ – macroeconomic and country-specific variables		
GDP	Quarterly real GDP growth (quarterly, percentage points)	*OECD (2020), Quarterly GDP (indicator). doi: 10.1787/b86d1fc8-en (Accessed on 14 June 2020)*
AAR	Annualised agreed rate by credit and other institutions in country *i* at time *t* (monthly, percentage points)	*ECB Statistical Data Warehouse http://sdw.ecb.europa.eu/*
EARNINGS	Median equalised household income in country *i* at time *t*. (yearly, in euros [€]). Log values.	*ECB Statistical Data Warehouse http://sdw.ecb.europa.eu/*
UNEM_RATE	Unemployment rate for each country (Monthly, seasonally adjusted, percentage points)	*OECD (2020), Unemployment rate (indicator). doi: 10.1787/b86d1fc8-en (Accessed on 14 June 2020)*

ECBRATE	ECB Deposit facility (Monthly, seasonally adjusted, percentage points)	*ECB Statistical Data Warehouse* *http://sdw.ecb.europa.eu/*
ESI	The EU Economic sentiment indicator (composite measure, average = 100). Log values	*Full business and consumer survey results, European Commission* https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en
Independent variables, $\mathbf{X}^{Demographics}$ **- variables representing demographic characteristics of countries**		
POPESTIMATE	Population of country *i* in year 2018. Log values.	*OECD (2020), Population (indicator). doi: 10.1787/d434f82b-en (Accessed on 24 July 2020)*
RELIGIOSITY	Percentage of adults who % of adults who are "highly religious" in country *i* (time-invariant, survey of 2018)	Religious Landscape Study (2018), Pew Research Center
Independent variables, $\mathbf{X}^{Technology}$ **- variables representing 'technology'**		
INTUSE	Percentage of individuals who have ever used the internet in country *i* at time *t* (for each year from 2015 to 2019 (yearly)	Digital economy and society, Eurostat https://ec.europa.eu/eurostat/web/digital-economy-and-society/overview
Independent variables, $\mathbf{X}^{Business}$ **- variables representing business sentiment**		
NPL	Gross non-performing loans in country *i* at time *t* (percentage of gross loans). Log values.	*ECB Statistical Data Warehouse* *http://sdw.ecb.europa.eu/*
INDEX	Average monthly stock market index values of country *i* at time *t*.Log values	Yahoo.Finance https://finance.yahoo.com/world-indices/

Table 6.2 reports descriptive statistics for the variables used in analyses of this Chapter. Mean value of issued monthly loans by Bondora and Mintos at each country was €1.21 million. These platforms issued, on average, 479 loans each month during the period under consideration. An amount of €482 thousand monthly issued loans was classified as bad loans at some point. Mean value for the average interest rate for loans in the sample is 13.92% deviating between the lower quartile of 6.09% and upper quartile of 14.45%. As the sample consists of loans from both Bondora and Mintos, the difference between the interest rates is substantial. Mintos loans are less risky and come with a buyback guarantee. Therefore, the Mintos average interest rate is 12.01% in the sample against the current advertised interest rate of 12.7%. On the other hand, Bondora loans are of high risk with no buyback guarantee. The average interest rate for Bondora loans is 35% against the advertised interest rate of 32%. In fact, it can be noted that the average interest rate and net return to investors are substantially different in P2P lending market. Platforms with their diversification and assessment of the loans try to offset default with higher interest spread. In this regard, the proper estimation of the probability of default is vital for P2P lending platform in terms of meeting required investor returns.

Mean average monthly income declared by borrowers is €2,366 with the standard deviation of €2,864. The median income is much lower at €1,510. This variation in household income is in the stark opposite of the US sample in Chapter 5, which did not have much deviation in terms of the income. This chapter is based on the cross-country database, and differences between the countries in terms of income disparity reveal important findings for this study. Average DTI scores for the sample are also in stark contrast to the LendingClub data set in Chapter 5. In the LendingClub database, average DTI score does not exceed 20% across all states of the US. Mintos and Bondora have very diverse loan portfolio with different risk categories. Thus, the database used in this chapter contains loans with varying DTI scores from 8% to 48%, in terms of the lower and upper quantiles. The average amount of loans issued is €2,291, with an average duration of 38.72 months. The median age of borrowers is 39.10 ranging from 29.46 of lower quantile to 48.42 of upper quantile. Other reported variables represent country-specific indicators.

Table 6.2: Descriptive statistics for variables included in regression analysis

Table 6.2 reports the descriptive statistics for variables included in the regression analysis. The variables include platform-specific, economic, demographic, technological and political characteristics. The variable descriptions are provided in Table 6.1.

Variables	Mean	Median	Std Dev	Upper Quartile	Lower Quartile
Platform-specific					
LOANVOL (€ thousands)	1210.6165	495.9000	1725.5534	6028.9000	40.5856
LOANCOUNT	479.8306	211.0000	629.0769	2309.0000	30.0000
BADLOANSVOL (€ thousands)	482.1723	248.2660	639.1005	2498.7880	0.2492
BADLOANSCOUNT	179.0717	98.0000	210.9609	726.0000	1.0000
AVEINTRATE (%)	13.9237	13.4872	4.9328	14.4529	6.0931
AVEINCOME	2366.1190	1510.2180	2864.3014	12847.2500	672.7547
AVEDTI (%)	15.4183	15.4150	15.6678	48.3774	8.0000
AVEAMOUNT	2291.4355	2264.5570	1259.7675	4904.1910	123.9360
AVEDURATION (months)	38.7239	43.2911	13.7434	56.1027	8.0674
AVERATING	5.9838	6.5000	1.2704	7.9241	3.5343
AVEAGE	39.4027	39.1061	4.1702	48.4186	29.4615
Economic variables					
INFLATION (%)	0.7471	0.2620	4.6397	8.3853	.02276
GDP (%)	0.6113	0.6777	0.8366	1.9374	-3.3093
AAR	11.7562	9.6000	6.6322	23.0600	2.9400
ESI	99.0694	99.7000	8.6299	111.3000	63.9000
EEI	99.7199	101.1000	9.9872	113.1000	57.8000
Demographic, technology and financial					
INTERNETUSERS (% of population)	88.1075	90.0000	6.2216	97.0000	76.0000
LASTINTUSE (% of population)	85.5440	87.0000	6.8599	95.0000	72.0000
INDEX	4818.2007	3499.5700	3904.2875	10840.1000	207.7600
INDCHANGE (%)	8.7673	8.0006	3.2279	10.8000	0.0304
EU_INDEX	3213.2803	3232.9100	314.9209	3703.5800	2248.7800
NPL	3.0482	3.1000	1.7095	8.1000	1.2000
POPESTIMATE (millions)	2.9403	1.3209	4.7396	5.5181	1.3209

This chapter reports a correlation matrix for the dependent, explanatory and control variables in Table 6.3. The table indicates low levels of Pearson's correlation coefficients for most of the variable pairs with few exceptions. However, these pairs are the different proxies of the same indicators. LOANVOLUME and LOANCOUNT have high correlation coefficients, as it is the case between the correlations of INTERNETUSERS and LASTINTUSET. These variables are not used in the same regression models. There is a high correlation between total loans and bad loans, which is predictable. Following the variable definitions in Chapter 4 (section 4.7) regression analysis in this chapter employs the measure of 'probability of default' and the logarithm of loan volumes. These transformations generally eliminate the problem of multicollinearity between the variables.

Table 6.3: Correlation matrix

Table 6.3 reports Pearson's correlation coefficients between the variables employed in regression analyses of this chapter. Significant correlations in bold. See Table 6.1 for variable definitions.

	LOANVOL	LOANCOUNT	BADLOANSCOUNT	BADLOANSVOL	AVEINTRATE	AVEINCOME	AVEDTI	AVEAMOUNT	AVEDURATION	AVERATING
LOANVOL	1.0000									
LOANCOUNT	**0.9463**	1.0000								
BADLOANSCOUNT	**0.7961**	**0.8140**	1.0000							
BADLOANSVOL	**0.8403**	**0.7388**	**0.9151**	1.0000						
AVEINTRATE	-0.0923	-0.0697	0.1732	0.0552	1.0000					
AVEINCOME	-0.1579	-0.1720	-0.1754	-0.1319	-0.0421	1.0000				
AVEDTI	-0.3550	-0.4054	-0.3775	-0.3105	0.0613	-0.3047	1.0000			
AVEAMOUNT	0.2751	0.1281	0.1853	0.3549	-0.1346	-0.3385	0.3251	1.0000		
AVEDURATION	0.4211	0.3973	0.5102	0.4959	0.1712	-0.4591	0.0869	0.6262	1.0000	
AVERATING	-0.4130	-0.4689	-0.2337	-0.2218	0.5791	0.1851	0.0344	-0.1573	-0.2374	1.0000
AVEAGE	0.3570	0.2667	0.4440	0.5006	0.2134	-0.2567	-0.1599	0.4709	0.6269	0.0405
INFLATION	0.0805	0.0849	0.0537	0.0662	-0.0106	0.0232	0.0052	0.0425	0.0405	0.0256
GDP	0.0588	0.1142	0.0733	0.0289	-0.0116	-0.2062	0.0606	-0.1019	0.0098	-0.1066
AAR	-0.0562	0.0448	-0.1787	-0.2392	-0.3757	0.0972	-0.0619	-0.4258	-0.4567	-0.3494
ESI	0.0041	0.0287	0.2400	0.1454	0.4040	-0.3502	-0.0016	0.0026	0.2798	0.1471
EEI	0.1645	0.1420	0.3461	0.3005	0.3821	-0.3918	-0.0429	0.1120	0.3762	0.0692
INTERNETUSERS	0.5149	0.4594	0.4975	0.5501	-0.0114	-0.3324	-0.0188	0.5975	0.6670	-0.4251
LASTINTUSE	0.4843	0.4303	0.5037	0.5430	0.0823	-0.3366	-0.0259	0.5986	0.7033	-0.3341
INDEX	0.2504	0.3670	0.3911	0.2092	0.4678	-0.2593	-0.2016	-0.0016	0.4308	0.2678
INDCHANGE	0.5445	0.7042	0.4283	0.3000	-0.2373	-0.1430	-0.3524	-0.0709	0.1427	-0.5213
EU_INDEX	0.3851	0.4067	0.4473	0.3691	0.2361	-0.0061	-0.2660	0.0709	0.4886	-0.1588
NPL	-0.3772	-0.3424	-0.3163	-0.3892	0.2756	-0.0458	0.1583	-0.3318	-0.2705	0.6196
POPESTIMATE	-0.0486	-0.0029	0.0610	-0.0355	0.3095	-0.1022	-0.0536	-0.1216	0.1017	0.3149

Table 6.3: Correlation matrix (Contd.)

	AVEAGE	INFLATION	GDP	AAR	ESI	EEI	INTERNETUSERS	LASTINTUSE	INDEX	INDCHANGE	EU_INDEX	NPL	POPESTIMATE
AVEAGE	1.0000												
INFLATION	0.0331	1.0000											
GDP	-0.0872	0.0120	1.0000										
AAR	-0.7011	-0.0231	0.3533	1.0000									
ESI	0.3105	-0.0165	0.5475	-0.0122	1.0000								
EEI	0.3811	-0.0287	0.5051	-0.0096	0.9234	1.0000							
INTERNETUSERS	0.0864	0.0439	-0.0349	-0.4999	0.0413	0.1753	1.0000						
LASTINTUSE	0.0723	0.0451	-0.0370	-0.5625	0.1023	0.2307	**0.9887**	1.0000					
INDEX	0.3480	0.1017	0.0921	-0.2913	0.3862	0.2969	0.0423	0.1164	1.0000				
INDCHANGE	0.0268	0.1171	0.1854	0.2406	-0.0421	-0.0663	0.2433	0.1979	0.4314	1.0000			
EU_INDEX	0.5051	0.0019	0.0457	-0.3339	0.2473	0.2489	0.4298	0.4513	0.4352	0.2189	1.0000		
NPL	-0.2525	0.0020	0.0457	0.0705	0.1492	0.0085	-0.0790	-0.0693	0.3700	-0.2641	-0.1452	1.0000	
POPESTIMATE	0.1059	0.0866	0.0526	-0.1407	0.1722	0.1404	-0.0895	-0.0462	0.3444	-0.1223	0.1642	0.3118	1

6.3 Results of baseline regression analysis

This chapter explores the impact of the borrower and country-specific factors on the probability of default. It particularly emphasises on inflation and interest rate as the main explanatory variables. Results of Chapter 5 documented significant positive impact of inflation and interest rate on the probability of default in the context of LendingClub (US) loan-book data. Results in Chapter 5 also fell in line with the limited literature on P2P lending (Serrano-Cinca et al., 2015) and a broad range of related literature in traditional finance (Espinoza and Prasad, 2010; and Beck et al., 2000; Klein, 2013; Skarica, 2014; Ghosh, 2015). This chapter extends this line of modelling by using the cross-country database. The database used in this chapter contains a wider range of borrower and country-specific variables. Chapter 5 used CPI inflation rates for state urban centres, and regional inflation when urban centre data were not available. On the contrary, using country-level monthly CPI inflation rate as a proxy for inflation provides more credibility for the results of this chapter. As it was in Chapter 5, this study uses average interest rate set for loans by the platform as a proxy for the interest rate. Regression analyses in this chapter follow the equations [8] and [9] (section 4.6.3) with a modified list of variables. Variables used in the regression analysis of this chapter are described in Table 6.1. Respective independent variables are lagged according to the equation [8] and [9] (section 4.6.3) as it was in Chapter 5.

Estimation results for baseline regression involving the probability of default as the dependent variable are reported in Table 6.4 and Table 6.5. Results are based on Random Effects Estimation with the constant, year and individual effects. Sampling size consists of 950 valid observations (N=950) across all models, as the panel data set is balanced for this Chapter. Countries included in the database also have a substantial amount of loans issued during the period under consideration. This feature of the data set does not require using the random bootstrapping as in Chapter 5. The complete balanced sample allows to safely conclude that the observed variations in variables are not attributed to outliers or missing observations.

The fit of the models in Table 6.4 based on the overall R-squared values varies around 0.25. These values indicate that independent variables collectively explain around 25% of changes in the dependent variable. The overall fit of the model considerably increased in this chapter if compared with Chapter 5. Since the data set is balanced and contain more borrower specific characteristics. The increased fit of the model enhances the significance of the main explanatory variables.

Models (1-4) in Table 6.4 depict the probability of default as a function of average interest rate (AVEINTRATE) and control variables. Average interest rate is significantly positive across all 4 models varying between 0.2244 and 0.2605. This finding indicates that interest rates significantly and positively affect delinquency rates represented by the probability of default (PD). It falls in line with the results documented in Chapter 5 and earlier study of Serrano-Cinca et al., (2015). Unlike the findings of Chapter 5, the coefficient for the interest rate is significantly lower in the analysis of the European market. This discrepancy might be attributed to the changes in modelling, as this chapter's regression analysis involved more borrower specific information. Nevertheless, this chapter provides more robust evidence that higher interest rates for loans lead to higher delinquency rates.

Table 6.4: Impact of average interest rate on the probability of default (baseline regression results)

Table 6.4 reports the results for the Fixed Effects panel data estimation representing the effect of platform-specific variable (average interest rate) on the probability of default with control variables. Estimations are based on equation [8]. Estimation model employs the proportion of bad loans to total loans (PD) as the dependent variable. All model specifications employ robust standard errors in parentheses
(* p<0.10, ** p<0.05, *** p<0.01).

	Model 1	Model 2	Model 3	Model 4
Variables	**DV= PD**	**DV= PD**	**DV= PD**	**DV= PD**
AVEINTRATE	0.2580***	0.2605***	0.2244**	0.2347***
	(0.0834)	(0.0834)	(0.0875)	(0.0878)
LOANVOL	0.2862***	0.2887***	0.2944***	0.2791***
	(0.0255)	(0.0255)	(0.0258)	(0.0280)
AVEINCOME	-0.8649***	-0.7888***	-0.7671***	-0.7589***
	(0.1055)	(0.1103)	(0.1115)	(0.1116)
AVEDTI	-0.0002	-0.0015	-0.0018	-0.0019
	(0.0021)	(0.0021)	(0.0022)	(0.0022)
AVEAGE	0.0541***	0.0504***	0.0491***	0.0503***
	(0.0088)	(0.0090)	(0.0090)	(0.0090)
AVEAMOUNT	-0.0757	-0.0310	-0.0168	0.0119
	(0.0535)	(0.0568)	(0.0578)	(0.0612)
AVEDURATION	-0.0080**	-0.0070**	-0.0069**	-0.0071**
	(0.0034)	(0.0034)	(0.0034)	(0.0034)
AVERATING	0.1429***	0.1506***	0.1184***	0.0951**
	(0.0351)	(0.0352)	(0.0425)	(0.0455)
GDP	0.0031	0.0042	0.0076	0.0080
	(0.0295)	(0.0294)	(0.0295)	(0.0295)
ESI	0.0271***	0.0255***	0.0236***	0.0237***
	(0.0046)	(0.0047)	(0.0049)	(0.0049)
INTERNETUSERS	0.0635***	0.0524***	0.0629***	0.0689***
	(0.0074)	(0.0088)	(0.0117)	(0.0125)
INDEX		-0.0750**	-0.0883***	-0.0973***
		(0.0321)	(0.0336)	(0.0342)
NPL			0.0503	0.0389
			(0.0372)	(0.0380)
POPESTIMATE				0.1436
				(0.1014)
Constant, Yr. & Ind. Effects	Yes	Yes	Yes	Yes
Overall R-squared	0.2514	0.2528	0.2533	0.2538
N	950	950	950	950

Table 6.5 reports the results of estimating the coefficients based on equation [9] with the inflation rate as an explanatory variable. Models (1-4) of Table 6.5, use the same set of control variables as in Table 6.4. Inflation rate (INFLATION) is the monthly measure of the change in seasonally adjusted consumer price index for respective countries in the database. The results of Model (1) indicate that the coefficient for inflation is significant and positive (0.0202). The coefficients for INFLATION are robust with the inclusion of INDEX, NPL and POPESTIMATE as additional control variables in Models (2-4). Coefficients for INFLATION are significantly positive varying from 0. 0202 to 0. 0259.

If every independent variable within the models in Table 6.4 and Table 6.5 is considered, some convincing results emerge from the findings. The coefficient for loan volume is consistent across the models (1-4) in both Table 6.4 and Table 6.5. Coefficients are significantly positive and vary between 0.2319 and 0.2944. This means that 1% increase in P2P lending loan volume increases the probability of default in the range of 23.19% to 29.44%. This finding is also consistent with the findings of Chapter 5 that yielded significant positive coefficients for loan volume in the range of between 0.1701 and 0.2014. AVEINCOME is found to have a significant negative coefficient ranging from 1.0681 to 1.2491. Accordingly, this chapter indicated that personal income growth reduces the probability of default. Age (AVEAGE) and loan rating (AVERATING) of borrowers were found to positively associate with the probability of default. DTI score (AVEDTI) yielded insignificant coefficients which are in stark contrast to the findings of Chapter 5. Analysis based on LendingClub data in Chapter 5 found that higher DTI score significantly increases the probability of default. Coefficients for AVEAMOUNT and AVEDURATION yielded significant negative coefficients indicating that the loans with higher principal value and longer duration have a lower probability of default.

Contrasting Chapter 5, this chapter used country-specific macroeconomic control variables which increased the credibility of the findings. Using the findings of baseline regression analysis, this study documents some important findings in terms of the impact of macroeconomic variables on the probability of default in P2P lending market. Coefficients for GDP is insignificant across all models and consistent with the results of Chapter 5. However, this chapter extended the indicators of economic development with an Economic Sentiment Indicator (ESI) as a proxy. Coefficients for

ESI are positive across all models in Table 6.4 and Table 6.5. Another novelty introduced in this chapter is the inclusion of financial market indicators. These indicators are stock market index (INDEX) and banking sector non-performing loans (NPL) for each country. INDEX has significant negative coefficients across all models in this chapter. The coefficient for INDEX varies between -0.1763 to -0.0750 across the six reported models in Table 6.4 and Table 6.5. However, NPL has insignificant coefficients in Models 3 and 4 in Table 6.4. Nevertheless, based on Models 3 and 4 of Table 6.5, where inflation is the dependent variable NPL has significant positive coefficients. Based on Model 4 of Table 6.5, a 1% increase in banking sectors' non-performing loans is associated with a 0.1134% increase in the probability of default in P2P lending market. The findings regarding INDEX and NPL might have significant implications in terms of understanding the interaction of P2P lending with the traditional financial markets. This issue is out of the scope of this thesis but might direct to promising fields for further research.

Table 6.5: Impact of inflation on the probability of default (baseline regression results)

Table 6.5 reports the results for the Fixed Effects panel data estimation representing the effect of platform-specific variable (average interest rate) on the probability of default with control variables. Estimations are based on equation [9]. Estimation model employs the proportion of bad loans to total loans (PD) as the dependent variable. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

	Model 1	Model 2	Model 3	Model 4
Variables	**DV= PD**	**DV= PD**	**DV= PD**	**DV= PD**
INFLATION	0.0202**	0.0221***	0.0203**	0.0259***
	(0.0083)	(0.0083)	(0.0083)	(0.0086)
LOANVOL	0.2484***	0.2575***	0.2622***	0.2319***
	(0.0289)	(0.0289)	(0.0289)	(0.0317)
AVEINCOME	-1.2491***	-1.1305***	-1.0819***	-1.0681***
	(0.1200)	(0.1243)	(0.1249)	(0.1250)
AVEDTI	0.0002	-0.0021	-0.0021	-0.0025
	(0.0022)	(0.0023)	(0.0023)	(0.0023)
AVEAGE	0.0811***	0.0736***	0.0703***	0.0729***
	(0.0094)	(0.0096)	(0.0096)	(0.0097)
AVEAMOUNT	-0.1884***	-0.1118*	-0.0989	-0.0419
	(0.0607)	(0.0643)	(0.0643)	(0.0688)
AVEDURATION	-0.0132***	-0.0117***	-0.0115***	-0.0123***
	(0.0038)	(0.0038)	(0.0038)	(0.0038)
AVERATING	0.1348***	0.1448***	0.0866**	0.0385
	(0.0298)	(0.0299)	(0.0347)	(0.0405)
GDP	0.0080	0.0076	0.0056	0.0061
	(0.0342)	(0.0342)	(0.0341)	(0.0341)
ESI	0.0289***	0.0256***	0.0231***	0.0231***
	(0.0051)	(0.0052)	(0.0052)	(0.0052)
INTERNETUSERS	0.0823***	0.0645***	0.0942***	0.1065***
	(0.0083)	(0.0097)	(0.0132)	(0.0143)
INDEX		-0.1257***	-0.1563***	-0.1763***
		(0.0354)	(0.0366)	(0.0376)
NPL			0.1301***	0.1134***
			(0.0397)	(0.0403)
POPESTIMATE				0.2628**
				(0.1140)
Constant, Yr. & Ind. Effects	Yes	Yes	Yes	Yes
Overall R-squared	0.2747	0.2783	0.2813	0.2828
N	950	950	950	950

6.4 Results for instrumental variable estimation

Following the regression modelling in Chapter 5, this chapter identifies areas of baseline regression that are subject to the problem of endogeneity. As it was in Chapter 5, reverse causality between two main explanatory variables (AVEINTRATE and INFLATION) and other variables in the model cannot be ruled out. Regression models in this chapter account for the year and individual effects (as in Chapter 5), in line with a broad range of country-specific indicators (distinctive from Chapter 5). Nevertheless, the model might have time-varying omitted variables that are correlated with the explanatory variables. Because of several macroeconomic indicators, explanatory variables AVEINTRATE and INFLATION might be driven by control variables such as GDP and LOANVOLUME, respectively. Following the method employed in Chapter 5, this thesis improves the baseline regression model by employing two-stage GMM Regression with instrumental variables. Table 6.6 presents the two-stage GMM regression results with instrumental variables for average interest rate and inflation. In Model 1 (Table 6.6), country-level unemployment rate (UNEM_RATE) and median net income (EARNINGS) were taken as instrumental variables for average interest rates. In Model (2), Annualised Agreed Rate (AAR) and European Central Bank Deposit facility rates (ECBRATE) were used as instrumental variables for inflation.

Interest rate yielded a significant positive coefficient with these instrumental variables. Table 6.6 documents that instrumental variables yielded significant coefficients. Average interest rate and inflation retain their significantly positive coefficients. This study tests the overall validity of the instruments by implementing the Sargan specification test, which, under the null hypothesis of valid moment conditions, is asymptotically distributed as chi-square (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). Instrument diagnostic tests also favour the use of two models in Table 6.6 with their respective instrumental variables. Thus, the average interest rate and inflation were found to have a significant positive coefficient in the baseline models and remained to be so in the model with instrumental variables.

Table 6.6: Impacts of average interest rate and inflation on the probability of default (two-stage GMM regression with instrumental variables)

Table 6.6 presents the two-stage GMM regression results with instrumental variables of average interest rate and inflation. All model specifications employ robust standard errors in parentheses (* *p*<0.10, ** *p*<0.05, *** *p*<0.01)

	Model 1: Average interest rate and the probability of default		Model 2: Inflation and the probability of default	
	1st Stage	2nd Stage	1st Stage	2nd Stage
	DV= AVEINTRATE	DV= PD	DV= INFLATION	DV= PD
AVEINRATE/INFLATION		1.4984***		0.2205**
		(0.3138)		(0.1086)
UNEM_RATE	0.0171***			
	(0.0012)			
EARNINGS	-0.0088***			
	(0.0012)			
AAR			0.0401***	
			(0.0136)	
ECBRATE			-0.0511***	
			(0.0068)	
LOANVOL	0.0614***	-0.0910***	-0.1700***	-0.2081***
	(0.0046)	(0.0335)	(0.0550)	(0.0319)
AVEINCOME	0.0941***	0.0550	-0.3467***	-0.2614***
	(0.0084)	(0.0494)	(0.1045)	(0.0724)
AVEDTI	0.0079***	0.0111***	0.0262***	0.0072**
	(0.0003)	(0.0025)	(0.0036)	(0.0031)
AVEAGE	-0.0187***	0.0132	0.1184***	0.0780***
	(0.0016)	(0.0102)	(0.0207)	(0.0137)
AVEAMOUNT	-0.2684***	-0.4085***	-1.4587***	-0.5135***
	(0.0107)	(0.0835)	(0.1303)	(0.1567)
AVEDURATION	0.0066***	0.0031	0.0380***	-0.0077
	(0.0006)	(0.0039)	(0.0079)	(0.0052)
AVERATING	0.2076***	0.2007**	0.2580***	-0.1067**
	(0.0058)	(0.0807)	(0.0736)	(0.0426)

Table 6.6: Impacts of average interest rate and inflation on the probability of default (Contd.)

GDP	-0.0957***	-0.1343***	0.5475***	0.1715**
	(0.0055)	(0.0420)	(0.0743)	(0.0750)
ESI	0.0049***	0.0389***	-0.0629***	-0.0114
	(0.0013)	(0.0077)	(0.0085)	(0.0082)
INTERNETUSERS	0.0066***	0.0997***	0.0986***	0.1281***
	(0.0017)	(0.0083)	(0.0222)	(0.0119)
INDEX	0.0942***	-0.1107***	0.6618***	-0.0987
	(0.0078)	(0.0308)	(0.0746)	(0.0742)
NPL	-0.0851***	0.0236	0.5800***	0.3666***
	(0.0058)	(0.0435)	(0.0701)	(0.0664)
POPESTIMATE	0.1245***	0.7130***	-2.0507***	-0.0246
	(0.0158)	(0.0964)	(0.1867)	(0.2488)
Constant, Yr. & Ind. effects	Yes	Yes	Yes	Yes
R-squared		0.1603		0.0216
N		950		950
Instrument diagnostics tests:				
Test of endogeneity: GMM distance test statistic of endogeneity		237.2818***		20.6085***
Weak identification test: (Cragg-Donald Wald F statistic)		128.3187		10.3229
Overidentification test: Sargan (1958) $\chi 2$		3.0254		0.8636
[*p*-value]		0.2345		0.3527

6.5 Regression results for subsamples of the data set

This chapter also replicates some of the analyses on subsamples of the data set and presents the differences between these subsamples in terms of functional form. As the data set is aggregated by individual countries, variations in terms of issued loans is widely different. As it was in baseline regression, analyses based on subsamples of the data set might document the consistency of findings of this study. Regression models were analysed within the context of loan volumes by dividing the sample into two groups based on the median loan volume. Two subsamples included observations with lower than median and higher than median loan volumes. Table 6.7 provides regression results for two models with respective two sample coefficient tests. The average interest rate tends to significantly affect bad loans in both subsamples. The coefficient for the average interest rate is 0.5688 for first subsample (lower than the median loan volume) and 0.0518 for second subsample (higher than median loan volumes). Two sample coefficient test indicates that the difference between the coefficients is significant with Chow test the chi-squared value of 8.06. This finding is in stark contrast with the findings of Chapter 5 based on LendingClub that did not find a significant difference in coefficients of interest rate across two subsamples. On the other hand, the effect of inflation on the probability of default behaved similarly with no significant difference between the subsamples. The coefficient for inflation is slightly higher for second subsample (higher than median volumes) but with insignificant Chow test chi-square statistic of 0.84. Thus, with the cross-country database, this chapter indicated the impact of the interest rate is more pronounced when the loan volumes are low. On the other hand, the impact of inflation does not significantly differ with the changes in the issued loan volumes.

Table 6.7: Impact of average interest rate and inflation on the probability of default (baseline regression for two subsamples based on aggregate loan volumes)

Table 6.7 presents the baseline regression results for two subsamples. Subsamples are based on the criteria of loan volumes in countries being higher or lower than the median level. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, ***p<0.01)

	Average interest rate and the probability of default		**Inflation and the probability of default**	
	Panel A: Lower than median loan volume	**Panel B: Higher than median loan volume**	**Panel A: Lower than median loan volume**	**Panel B: Higher than median loan volume**
Variables	**DV = PD**	**DV = PD**	**DV = PD**	**DV = PD**
AVEINRATE/ INFLATION	0.5688**	0.0518***	0.0288	0.0310***
	(0.2228)	(0.0127)	(0.0181)	(0.0080)
LOANVOL	0.6419***	0.0352***	0.7008***	0.0414***
	(0.0506)	(0.0058)	(0.0632)	(0.0062)
AVEINCOME	-1.3846***	0.1612***	-1.5654***	0.1517***
	(0.2503)	(0.0111)	(0.2611)	(0.0125)
AVEDTI	-0.0004	-0.0012***	-0.0037	-0.0014***
	(0.0042)	(0.0003)	(0.0043)	(0.0003)
AVEAGE	0.0618***	-0.0069***	0.0478***	-0.0066***
	(0.0162)	(0.0013)	(0.0176)	(0.0013)
AVEAMOUNT	0.5351***	0.0572***	0.5868***	0.0730***
	(0.1301)	(0.0119)	(0.1336)	(0.0126)
AVEDURATION	0.0154**	0.0015***	0.0287***	0.0026***
	(0.0068)	(0.0004)	(0.0080)	(0.0004)
AVERATING	-0.1467	0.0569***	-0.2352**	0.0312***
	(0.1030)	(0.0055)	(0.1099)	(0.0034)
GDP	-0.0964	0.0212***	-0.1768**	0.0296***
	(0.0652)	(0.0030)	(0.0751)	(0.0036)
ESI	0.0663***	0.0108***	0.0947***	0.0105***
	(0.0097)	(0.0006)	(0.0112)	(0.0006)
INTERNETUSERS	0.1117***	0.0128***	0.1664***	0.0207***
	(0.0285)	(0.0030)	(0.0289)	(0.0032)
INDEX	-0.2843**	0.0358***	-0.5256***	0.0323***
	(0.1346)	(0.0035)	(0.1340)	(0.0037)
NPL	-0.0489	-0.0048	-0.1121*	0.0223**
	(0.0573)	(0.0089)	(0.0654)	(0.0097)
POPESTIMATE	1.0831***	0.0775***	2.1174***	0.0776***
	(0.2962)	(0.0099)	(0.3011)	(0.0112)
Constant, Yr. & Ind. effects	Yes	Yes	Yes	Yes
R-squared	0.3473	0.3025	0.3115	0.3067
N	530	420	530	420
Two sample coefficient test: (Chow test chi-square statistic for Aveinrate/Inflation)		8.06***		0.84

This chapter also analysed the functional form in the context of subsamples based on religiosity level of countries under consideration. Table 6.8 reports the results of the regression for these subsamples. The first subsample includes observations with higher than the median religiosity, while the second subsample includes observations with lower than the median level of religiosity. Following the religiosity indicator used in Chapter 5, this chapter used the survey results from the Pew Research Center (2018) for individual countries. The coefficients for average interest rates are significantly positive for both subsamples. The coefficient for the average interest rate for low religiosity subsample is higher than the high religiosity states. This finding falls in line with the findings of Chapter 5. This documents that the average interest rate affects the probability of default at a higher magnitude in low religious states compared with high religious states. Similar to the findings of Chapter 5, the difference between the coefficients are insignificant, reflected in the two-sample coefficient test. The insignificance of the Chow test chi-square statistic prevents this study of drawing a strong conclusion in this regard.

On the other hand, the findings regarding inflation are supported by the significance of Chow test chi-square in both Chapter 5 and Chapter 6. Inflation proved to be significantly different among two subgroups based on religiosity, as reported in Table 6.8. Inflation coefficient is negative for high religiosity subgroup and positive for low religiosity subgroup. Two sample coefficient tests for inflation yielded a chi-square statistic of 7.73, that indicates a significant difference in coefficients. This result falls in line with the analyses in Chapter 5 and builds a strong argument for the impact of inflation on the probability of default. Inflation has a significant negative impact on bad loans among high religious states. On the contrary, the impact is significantly positive among low religious states.

Table 6.8: Impact of interest rate and inflation on the probability of default (for subsamples of high and low religious countries)

Table 6.8 presents the baseline regression results for two subsamples. Subsamples are drawn based on the religiosity of countries. Median religiosity level is based on the variable of 'Religiosity'. Refer to Table 6.1 for the variable description. All model specifications employ robust standard errors in parentheses (* *p*<0.10, ** *p*<0.05, *** *p*<0.01)

	Average interest rate and the probability of default		**Inflation and the probability of default**	
	Panel A: High religiosity	**Panel B: Low religiosity**	**Panel A: High religiosity**	**Panel B: Low religiosity**
	DV= PD	DV= PD	DV= PD	DV= PD
AVEINRATE/ INFLATION	0.0791*	0.0972***	-0.0100***	0.0015
	(0.0468)	(0.0137)	(0.0021)	(0.0011)
LOANVOL	-0.1882***	-0.0313***	-0.2164***	-0.0157***
	(0.0084)	(0.0035)	(0.0082)	(0.0035)
AVEINCOME	0.1137***	0.0541***	0.1278***	0.0473**
	(0.0120)	(0.0185)	(0.0110)	(0.0228)
AVEDTI	0.0027***	0.0004**	0.0019**	0.0008***
	(0.0008)	(0.0002)	(0.0008)	(0.0002)
AVEAGE	0.0251***	-0.0042***	0.0220***	-0.0075***
	(0.0027)	(0.0012)	(0.0027)	(0.0013)
AVEAMOUNT	0.2086***	0.0372***	0.2018***	-0.0103
	(0.0193)	(0.0097)	(0.0189)	(0.0094)
AVEDURATION	0.0030***	0.0014***	0.0083***	0.0013***
	(0.0011)	(0.0004)	(0.0012)	(0.0004)
AVERATING	-0.0526***	-0.0361***	-0.0557***	-0.0052
	(0.0132)	(0.0057)	(0.0117)	(0.0047)
GDP	0.0232***	0.0473***	0.0329***	0.0411***
	(0.0060)	(0.0053)	(0.0069)	(0.0062)
ESI	-0.0040***	0.0076***	-0.0047***	0.0109***
	(0.0010)	(0.0006)	(0.0010)	(0.0007)
INTERNETUSERS	0.0305***	-0.0048***	0.0326***	-0.0037**
	(0.0047)	(0.0014)	(0.0050)	(0.0016)
INDEX	0.0605***	-0.0860***	0.0546***	-0.1458***
	(0.0139)	(0.0312)	(0.0138)	(0.0370)
NPL	-0.0415**	0.0160***	-0.0274	0.0030
	(0.0186)	(0.0036)	(0.0173)	(0.0039)
POPESTIMATE	0.0000	-0.0343*	0.0000	0.0135
	(.)	(0.0204)	(.)	(0.0241)
Overall R-squared	0.0686	0.0635	0.0679	0.0565
N	410	540	410	540
Two sample coefficient test: (Chow test chi-square statistic for Aveinrate/Inflation)		0.16		7.73***

6.6 Compliance of results with earlier research findings

Extending on the notions developed in Chapter 5, this chapter tested the effect of various determinants on P2P loan delinquencies in a cross-country study setting. Faced with the limited literature to cross-validate the results, this study used a triangulation approach to enhance the validity of the findings. The findings of Chapter 5 were tested in cross-country study settings in this chapter with the database consisting of a wider range of independent variables. Heterogeneity between the panels was more pronounced in the European cross-country database compared with cross-state US data set. Proxy for inflation (one of the main explanatory variables) was largely improved in this chapter. Chapter 5 used urban centre and regional inflation as a proxy for state-level inflation that was not the perfect measure of reflecting the true inflation level in each state. However, Chapter 5 improved in this regard and employed country-level inflation indicators. This improvement reflects the true level of inflation in each country. The results of this chapter mainly solidified the evidence documented in Chapter 5. Higher inflation and interest rate significantly increase the probability of default in both state-wide and inter-country context.

A significant impact of interest rate on P2P lending loan probability of default was documented in the only available study of Serrano-Cinca et al. (2015). The results of this chapter fall in line with the findings documented in Serrano-Cinca et al. (2015). The results comply with a group of empirical studies in traditional financial markets (Espinoza and Prasad, 2010; and Beck et al., 2000), but contradict with the studies of Jakubık (2006), Goel and Hasan (2011), and Ghosh (2015). The significant positive coefficient for inflation remained consistent across the models of Chapter 5 and 6. This result also fits into the broad empirical evidence from commercial banks (Klein, 2013; Skarica, 2014; Ghosh, 2015).

This chapter supported the finding of Chapter 5 in terms of the relationship between inflation and the probability of default based on religious adherence. This study is unique in terms of providing evidence that inflation has a significantly different relationship with the probability of default based on the degree of religiosity. Chapter 5 proved this relationship in the context of the cross-state study. This chapter, on its turn, widened the scope of this finding into the international perspective. Therefore, this study is unique in this regard and provides additional insight into the aspect of religiosity not only in P2P lending market but in the financial market, overall.

This chapter used more specific indicators representing the macroeconomic environment and business sentiment. This change in the modelling revealed several relationships that might have significant practical implications and open the room for further research. Similar to the findings of Chapter 5, GDP was found to have a positive but insignificant impact on borrower delinquencies. Other variables were not used in Chapter 5 because of the data access constraints. This chapter employed NPL and INDEX to explore the interaction between the traditional financial markets and P2P lending market. Existing literature largely lack in this regard with only one known study empirically examining the interaction between these markets. Jagtiani and Lemieux (2018) analysed the penetration of P2P lending loans in various geographical areas of the USA. They indicated that P2P consumer lending penetrates into areas with relatively underserved banking markets and where the local economy is not performing well. However, this study can refer to a number of studies exploring the relationship between traditional and alternative lending markets. Buchak, Matvos, Piskorski, and Seru (2018) and Thakor (2020) highlighted that alternative investments prosper at places where the traditional lending channels are not developed or where traditional banks are faced with more regulatory constraints. In this study, the variable representing the stock market development (INDEX) yielded significant negative coefficients. Accordingly, the author concludes that an increase in the stock market decreases delinquencies in P2P lending market. Another variable that is related to financial development, namely NPL, has significant positive coefficients throughout baseline regression results. This indicates that an increase in non-performing loans directly transfers to P2P lending market by increasing delinquencies. The impact of INDEX and NPL requires further robustness tests and opens wide room for further research. This aspect of the study is duly highlighted in the last Chapter in line with the limitations of this thesis.

6.7 Generality of findings

This study is one of the first empirical investigations of P2P lending markets. This chapter investigated multiple factors related to the default risks of online P2P platforms based on Mintos and Bondora loan-book data. Expanding on the findings of Chapter 5 the author relied on extended cross-country data set with an extended range of variables. Cross-country database with several variables was not available for the USA market, which limited the generality of the findings in Chapter 5. Many of the findings in this chapter supported the conclusions made in Chapter 5. This chapter also revealed several additional results that shed light on the online P2P lending literature by identifying the relationship of this market with traditional financial markets.

The main analyses in this chapter were based on the sample database from Bondora and Mintos covering the period from 2015 to 2019. Though these platforms are based in Estonia and Latvia, they issue loans and accept investments across the EU. Therefore, the findings should still be relevant to other P2P lending platforms in the EU. A generalisation of findings for the year 2020 and beyond should also be relevant. This is because of the model framework from the well-proven traditional financial markets and the never-changing incentives of investors. Nonetheless, the generalisation of the study's findings should be applied with caution during periods of financial distress. The year 2020 is proving to be a challenging period for the P2P lending market. The ongoing COVID-19 pandemic, turmoil in the traditional financial markets and the resulting economic recession created major problems for the burgeoning industry. This study mainly explores the insolvency of the borrowers, which is expected to skyrocket as the current adverse economic conditions persist. The findings of this study related to macroeconomic variables may offer some clues about the expected impact of economic conditions on P2P lending market. At the same time, the full scale of the problem related to insolvency cannot be observed in the short-term because of the various government policies shielding borrowers. What can be explored is the liquidity risk faced by platforms and investors in the short term. Thus, the author introduced changes to the scope of this thesis by exploring the burning issues faced by the industry. Therefore, the next chapter explores the liquidity risk in P2P lending market when faced with contagion type external conditions.

Chapter 7:

Impact of COVID-19 Pandemic on P2P Lending Market

7.1 Background of the topic

The development of technology-enabled financing (Fintech) plays a vital role in securing funds for the development of small businesses, small consumer borrowers and the overall economy. During the last decade, the market for Fintech experienced rapid expansion. As a critical response to the GFC of 2007–2008, digital P2P lending burst onto the world scene together with the Cryptocurrencies and alternative financial instruments. Specifically, P2P lending practices became innovative in terms of their ability to remove the intermediary from the process and raise debt-funding from investors via an internet-based platform. Growth rates of the market are impressive and relatively low barriers to market entry combined with low market interest rates made this sector very dynamic. However, potential risk factors resulting from variability of defaults, loan recovery, platform failure, fraud or cybercrime pose threat to investors and platforms itself (Milne & Parboteeah, 2016). One of the early indications of vulnerability came in 2018 when the wave of defaults swept across Chinese P2P lending market (Wildau & Jia, 2018). This caused the withdrawal of funds by investors and the collapse of platforms not being able to maintain liquidity. Most of the P2P lending platforms diversify across a large number of borrowers and maintain a certain level of 'hardship funds'. These measures allow them to protect themselves against the borrower defaults and maintain the required level of liquidity (Cumming & Hornuf, 2018). What remains unprotected is loan loss and liquidity risk over the business cycle. At the same time, the current economic downturn as a result of COVID-19 pandemic increased the likelihood of unsustainable losses by the industry. There is a need for better understanding of the dynamics of successful P2P lending under the conditions of financial distress. Thus, the central question of this chapter is: *How did the COVID-19 affect P2P lending market liquidity?*

7.2 Chapter outline

This chapter presents an empirical examination of P2P lending market during the COVID-19 pandemic. In this chapter, the author empirically investigates main factors influencing the liquidity risk under the financial distress of the market. The data set consisting of secondary market listings on Bondora's P2P lending platform based in Estonia are compiled. Bondora is one of the early P2P lending platforms in Europe launched in 2008. Bondora's Secondary Market is the liquidity management feature offered for investors and creates a complementary marketplace for issued loans. This secondary marketplace offers an opportunity to exit the investment early and liquidate the loan portfolio. This chapter examines the secondary market listings for the period from January 2016 to June 2020. This platform is considered to be very suitable for the purpose of this chapter, as it is one of the largest cross-border P2P lending platforms working with investors in over 88 countries (including all EU countries).

Prior studies on P2P lending or crowdfunding did not examine the issues related to liquidity risk and behaviour of investors under the adverse economic conditions such as COVID-19. For over a decade, P2P lending platforms were benefitted from favourable external conditions, and data were simply not available for observing the tendencies under financial distress. In fact, 2020 is expected to be the first year for P2P lending market with a global economic downturn. However, the context of the issues raised in this chapter can be evaluated by relying on traditional financial and economics literature. The literature related to this topic is discussed in the Literature Review (Chapter 3) of this thesis. Literature indicates that pandemics have an enormous economic cost that can impact financial systems (Haacker, 2004; Santaeulalia, 2008; Yach, Stuckler, and Brownell, 2006). Specifically, pandemics are linked with the collapse of the banking sector, lower lending to the poor and higher deposit withdrawals (Leoni, 2013; Lagoarde-Segot and Leoni, 2013; Skoufias, 2003). Agosto and Giudici (2020) highlight that the advancement in digital finance increased the exposure of financial markets to stressful events such as COVID-19. Hence, the impact of COVID-19 on the financial sector is evident with a significant effect on financial technologies, such as crowdfunding and P2P lending.

To this end, in this chapter, the author provides early evidence of the pandemic induced exposure to liquidity risk in P2P lending market. This chapter examines the impact of the pandemic, as well as the related uncertainty on P2P lending investor sentiment. Firstly, it presents a regression model employing the daily number of listings and the probability of successful selling as continuous dependent variables. The data highlights that the number of listings and related volatility in Bondora's Secondary Market substantially increased around the early days of the pandemic. Secondly, this chapter analyses the potential impact of COVID-19 on P2P lending industry using the method of survival analysis. For survival analysis, this study uses all listings in 2020 with the outcome of the listings as a binary dependent variable, which can be employed to understand the dynamics of external shocks in P2P lending markets. The proposed model allows to better predict and monitor the impact of external shocks like COVID-19 pandemic. The models in this chapter indicate that despite increased volatility, the probability of success[17] increased during the period of a pandemic. However, it should be noted that the findings of this study should be used with caution because of the limitations imposed by third parties and rapid changes happening in the industry.

The remainder of the chapter proceeds as follows. The next section broadens Hypothesis 3, developed in the Literature review (section 3.6). Section 7.4 briefly explains Bondora P2P lending platform. Section 7.5 consists of descriptive analysis and section 7.6, 7.7 and 7.8 provide a discussion of empirical analysis. This chapter concludes with section 7.9 by highlighting a number of concluding remarks.

7.3 Developing specific hypotheses for this chapter

It is expected that current pandemic negatively affects the liquidity of P2P lending platforms by creating 'bank-run' type scenario (Peckham, 2013). Following the typical behaviour in traditional financial markets, pandemic triggered 'herding behaviour' among P2P lending market investors that rushed to turn their stakes into cash in masses. Accordingly, this chapter hypothesises that the announcement of COVID-19 as a pandemic by the World Health Organization (WHO) and the subsequent increase in cases boosted the number of listings in Bondora's Secondary

[17] This study defines the probability of success as the probability of successfully selling the stake in loan by the investor at the Bondora's Secondary Market

Market. This chapter also predicts that the developments related to the pandemic reduced the probability of successfully 'cashing-out' investor holdings in loans from Bondora's P2P lending. To this end, the hypotheses tested in this chapter are as follows:

COVID-19 pandemic and secondary market listings:

H3a: The announcement of the COVID-19 pandemic by the WHO significantly increased the daily number of listings in Bondora's Secondary Market.

H3b: The increase in daily COVID-19 case numbers significantly increased the daily number of listings in Bondora's Secondary Market.

H3c: The increase in daily numbers of COVID-19-related deaths significantly increased the daily number of listings in Bondora's Secondary Market.

COVID-19 pandemic and probability of successful listing outcome:

H3d: The announcement of the COVID-19 pandemic by the WHO significantly reduced the probability of success in Bondora's Secondary Market.

H3e: The increase in daily COVID-19 case numbers significantly reduced the probability of success in Bondora's Secondary Market.

H3f: The increase in daily numbers of COVID-19-related deaths significantly reduced the probability of success in Bondora's Secondary Market.

7.4 About Bondora

As it is highlighted in Chapter2 P2P lending market in continental Europe is experiencing great continuous growth. Paired with its still developing regulations, the EU represents an excellent opportunity for analysing current tendencies in P2P lending. Within the framework of this chapter, the study uses the P2P lending platform data from Bondora Capital OÜ based in Estonia. Nevertheless, Bondora is a marketplace for P2P consumer lending that covers most of the EU countries. Its marketplace allows users to invest in loans granted through the Bondora Group to borrowers in Estonia, Finland and Spain. Bondora has historically financed the loans by selling the associated receivables to a retail investor base drawn from 40 countries around the world, including all countries of EU. Bondora also publicly discloses of its financial records, including the full loan-book and secondary market transactions. In this regard, the data available from Bondora is extremely suitable for analysing investor sentiments across Europe during the pandemic.

Bondora has been in business since 2009 and is one of the leading non-bank digital consumer loan providers in Continental Europe. The consumer loans that Bondora offers are marketed in Finland, Spain and Estonia through a fully digital process supported by advanced credit analytics and in-house servicing. All loans are unsecured consumer loans with principal amounts of €500 to €10,000 and repayment terms ranging from three to 60 months. It is possible to automate investments and trade loans in a secondary market. The secondary market offers an opportunity to exit the investment early and can be equivalent to cashing out a financial instrument in traditional financial markets.

Figure 7.1 depicts the loan portfolio of Bondora from January 2019 to June 2020 with the share of overdue loans. Following the financial market turmoil as a result of COVID-19 pandemic, Bondora experienced certain disruptions in the loan portfolio (Tomberg, 2020a). Certain actions were undertaken by the company to maintain steady returns for investors during these times. Loan originators based in Finland and Spain were suspended; partial payout feature of ‘Go & Grow’ was automatically activated for most of the investor withdrawals; and new loan applications were stringently reduced (Bondora, 2020). As depicted in Figure 7.1, the volume of loans substantially dropped from April 2020. However, this was the result of reduced investor funding rather than the fall in loan applications (Tomberg, 2020b).

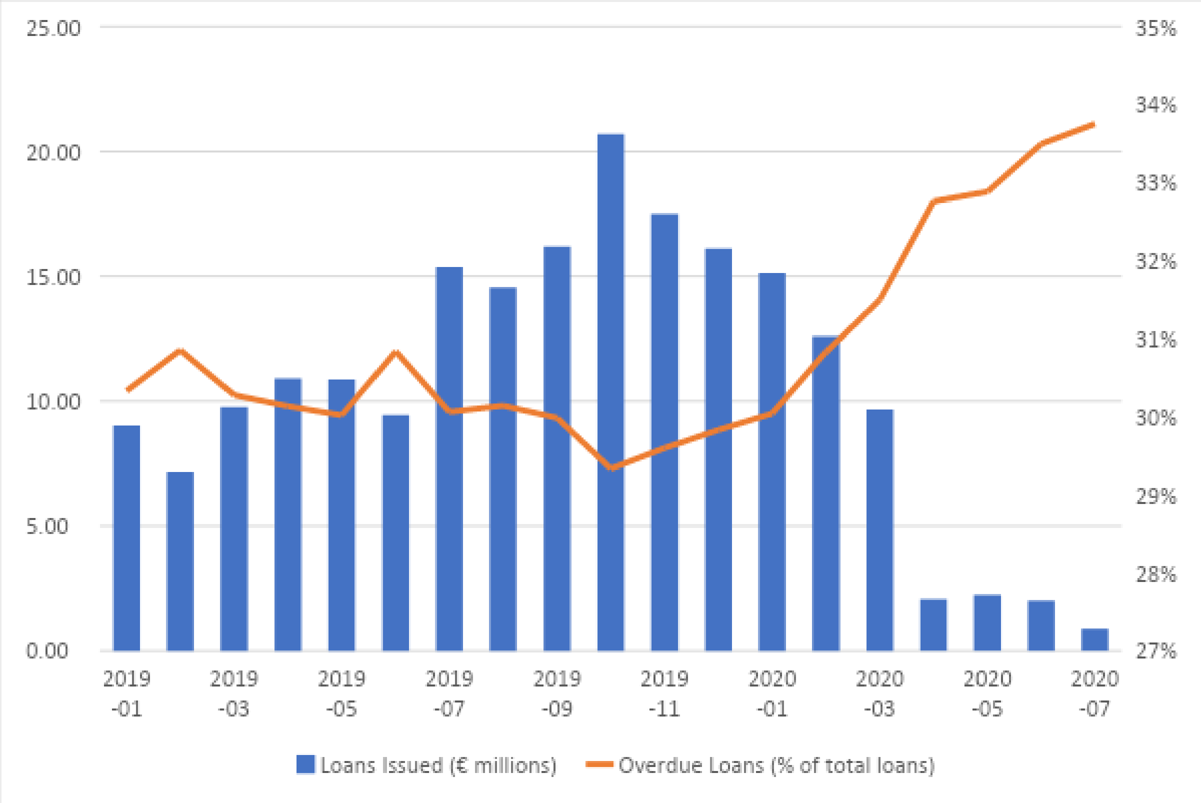

Figure 7.1: Loan portfolio and overdue loans issued by Bondora (Jan 2019–June 2020)

Source: Bondora (2020)

7.5 Descriptive analysis

Bondora provides its comprehensive secondary market and loan book data set with diverse features of each loan and loan holder. The author combined secondary market transactions from 2016 to 2020 that amounted in over 5 million observations. Then this database was aggregated by the number of failed and successful listings by listed date (daily observations) and country of loan origination. The data set of secondary market transactions were aggregated with country-specific variables obtained from other sources. For example, the study added data on EU Economic Sentiment Indicator (ESI) for each country of loan origination that was obtained from the statistical database of the Directorate-General for Economic and Financial Affairs of the European Commission. The aggregated database consists of 1729 valid observations with some missing observations. Missing observations, because of non-availability of data, reduced the sampling size (N) and formed unbalanced panel data.

This problem considerably reduces the degrees-of-freedom (df) in the regression analysis.

Observations in this modified database do not allow to fully grasp the gravity of the situation because of the small sample size that coincides with the pandemic period. This database also does not include important loan and borrower characteristics, which might create the problem of an omitted variable. Therefore, in the second stage of analysis, this chapter uses all the secondary market listing outcomes as a binary dependent variable. The study combined each of the listings with the country-specific variables and corresponding loan details from the loan book data set. The updated database consists of 17 explanatory variables, with over 5 million observations. It safeguards against the problem of omitted variables and substantially increases the degrees-of-freedom (df) in the regression analysis. Each of the listings in the database also contains the observations for starting and ending time of the listing. This information allows the author to examine the data using survival analysis, which facilitates estimating the timing of failure. Table 7.1 provides the table with the description of all variables used in this study.

Table 7.1: Description of variables used in Chapter 7

Variable	Description of variable	Source
Dependent variables		
LISTINGS	Number of daily listings at Bondora's Secondary Market at time *t* (daily observations, continuous variable).	*Bondora*
PROB_SUCCESS	Probability of success at Bondora's Secondary Market at time *t* (daily observations, continuous variable). Probability success of the listing at time *t* is calculated as in equation [17].	*Bondora*
RESULT_DUMMY	The reason why the listing was sold or removed from the Bondora's Secondary Market. Dummy variable equal to 1 if the listing is 'successful' and 0 otherwise (cancelled or failed)	*Bondora*
STATUS_DUMMY	Current status of individual loan. Dummy variable equal to 1 if the loans is overdue and 0 otherwise (current or repaid).	*Bondora*
LATEDAYS	The number of days the loan had been in debt at the date of the listing (log values).	*Bondora*
AMOUNT	Value of individual loan. (log values).	*Bondora*
Independent variables, pandemic indicator variables		
PANDEMIC_DUMMY	Variable representing the COVID-19 pandemic. Dummy variable equal to 1 for the dates later than 11 March, 2020 (The date WHO declared COVID-19 as pandemic) and 0 otherwise;	*World Health Organization (2020)*
CASES	Variable representing the COVID-19 pandemic. Change in the number of reported daily cases of COVID-19 in country *i* at time *t* (daily observations, log values).	*World Health Organization (2020), Johns Hopkins University & Medicine (2020)*
DEATHS	Variable representing the COVID-19 pandemic. Change in the number of reported daily COVID-19 related deaths in country *i* at time *t* (daily observations, log values).	*World Health Organization (2020), Johns Hopkins University & Medicine (2020)*
COVID_INDEX	Government Response Stringency Index: composite measure based on nine response indicators to COVID-19 pandemic, including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest, log values).	*Thomas Hale, Sam Webster, Anna Petherick, Toby Phillips, and Beatriz Kira (2020). Oxford COVID-19 Government Response Tracker, Blavatnik School of Government.*
Independent variables, borrower-specific variables		
INTEREST	Maximum interest rate accepted in the loan application.	*Bondora*
DTI	DTI score of borrower.	*Bondora*
INCOMETOTAL	Annual income of borrower (log values).	*Bondora*

LOANDURATION	Duration of loan (log values).	*Bondora*
RATING	Rating of loan. Bondora Rating issued by the Rating model ranging between AA and HR (https://www.bondora.com/blog/introducing-bondora-rating/)	*Bondora*
AGE	Age of borrowers when signing the loan application.	*Bondora*
GENDER	Gender of borrower: 0-Male, 1- Woman, 2-Undefined.	*Bondora*
RESTRUCTURED	Dummy variable representing the restructuring of a loan. Equal to 1 if the original maturity date of the loan has been increased by more than 60 days, 0 otherwise.	*Bondora*
DISCOUNTRATE	The discount/mark-up set by the seller.	*Bondora*
PRINCIPAL_DIFF	The difference between the outstanding principal at 'StartDate' and principal at 'EndDate' of the listing.	*Bondora*
EMP_DUR	Employment time of borrower with the current employer: 0-Trial period, 1-Up to 1 year, 2-Up to 2 years, 3- Up to 3 years, 4- Up to 4 years, 5- Up to 5 years, 6-More than 5 years, 7-Retiree.	*Bondora*
EDUCATION	Education level of borrower: 1-Primary education, 2-Basic education, 3-Vocational education, 4-Secondary education, 5-Higher education.	*Bondora*
HOMEOWNERSHIP	Home ownership type of the borrower: 1-Owner, 2-Living with parents, 3-Tenant, pre-furnished property, 4-Tenant, unfurnished property, 5-Council house, 6-Joint tenant, 7-Joint ownership, 8-Mortgage, 9-Owner with encumbrance, 10-Other.	*Bondora*
Independent variables, macroeconomic and country-specific variables		
AAR	Annualised agreed rate by credit and other institutions in country i at time t (monthly, percentage points)	*ECB Statistical Data Warehouse http://sdw.ecb.europa.eu/*
ESI	The EU Economic sentiment indicator (composite measure, average = 100, log values)	*Full business and consumer survey results, European Commission* https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en
POP	Population of country i in year 2018 (log values).	*OECD (2020), Population (indicator). doi: 10.1787/d434f82b-en*
INDEX_CHANGE	Change in average monthly stock market index values of country i at time t (monthly, percentage points).	Yahoo.Finance, https://finance.yahoo.com/world-indices/

Figure 7.2 provides a breakdown of the distribution of the daily number of listings in the sample database based on each month of 2020. Figure 7.2 indicates that the daily listings considerably increased during March. This period was characterised by the tumultuous behaviour of investors as the coronavirus scare unfolded and the WHO declared COVID-19 as a pandemic. Figure 7.2 uses a box plot to indicate considerably high average (median) daily listings in March 2020 compared to January and February 2020. During March 2020, the changes in daily listings were also extremely high, as depicted by the standard deviation and quartiles. The box plot in Figure 7.2 also indicates that the numbers relatively stabilised by April and fell below pre-pandemic levels in May. However, the fall in secondary market activity was the result of restrictions imposed by Bondora rather than the change in investor sentiment (Tomberg, 2020a).

Impact of disruptions related to the news cycles of the pandemic is particularly visible if the daily listings are presented in the form of a line chart. Figure 7.3 depicts the daily number of listings as a line chart with the date of the pandemic declaration highlighted in dash line. The line chart visually indicates of contagion type conditions in Bondora’s Secondary Market around the dates of declaration of a pandemic. As the COVID-19 related negative news broke out, there were sharp and sudden spikes in secondary market listings. These types of spikes are extremely detrimental for P2P lending market investors, as the market liquidity is much lower than the traditional financial markets. Crisis measures implemented by Bondora such as withdrawal limits safeguarded liquidity of the platform to a certain degree. Nevertheless, restrictions are effective in the short-term and might backfire in the long-term as the liquidity risk transforms into insolvency. P2P lending platforms require certain long-term changes in their risk assessment and management, considering changed conditions in a business environment. The next section of this chapter empirically analyses the Bondora’s Secondary Market listings data that explains the changes in investor sentiment over the pandemic period. The findings also identify factors that further shape risk management in P2P lending market post-pandemic.

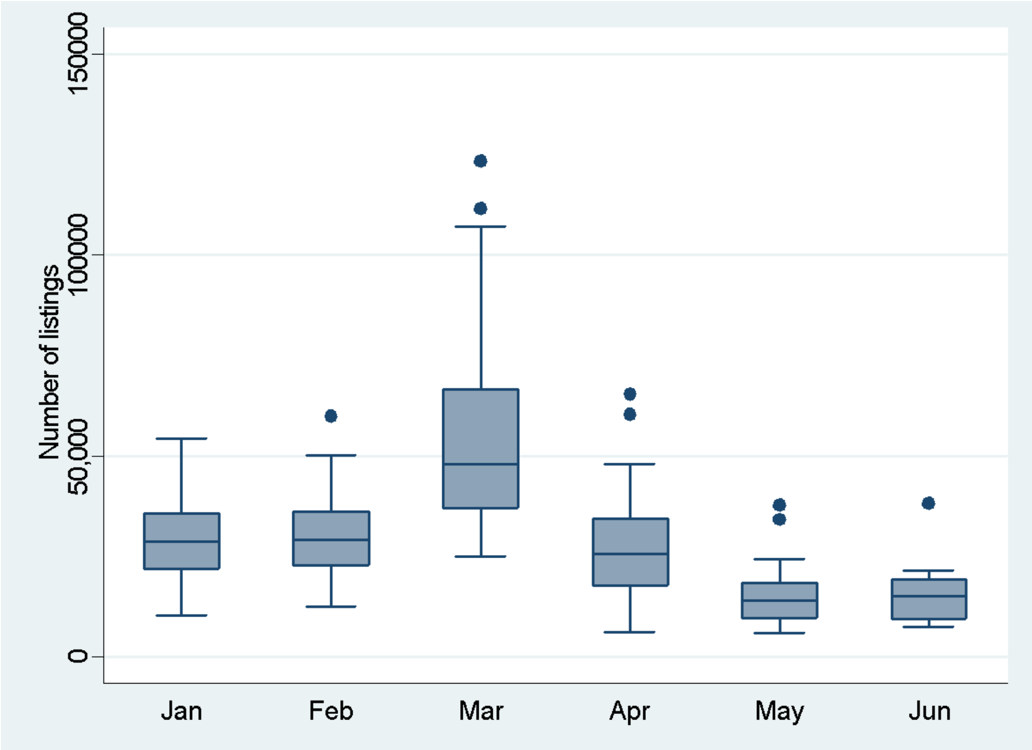

Figure 7.2: Monthly distribution of daily number of listings in Bondora's Secondary Market (January 2020–June 2020)

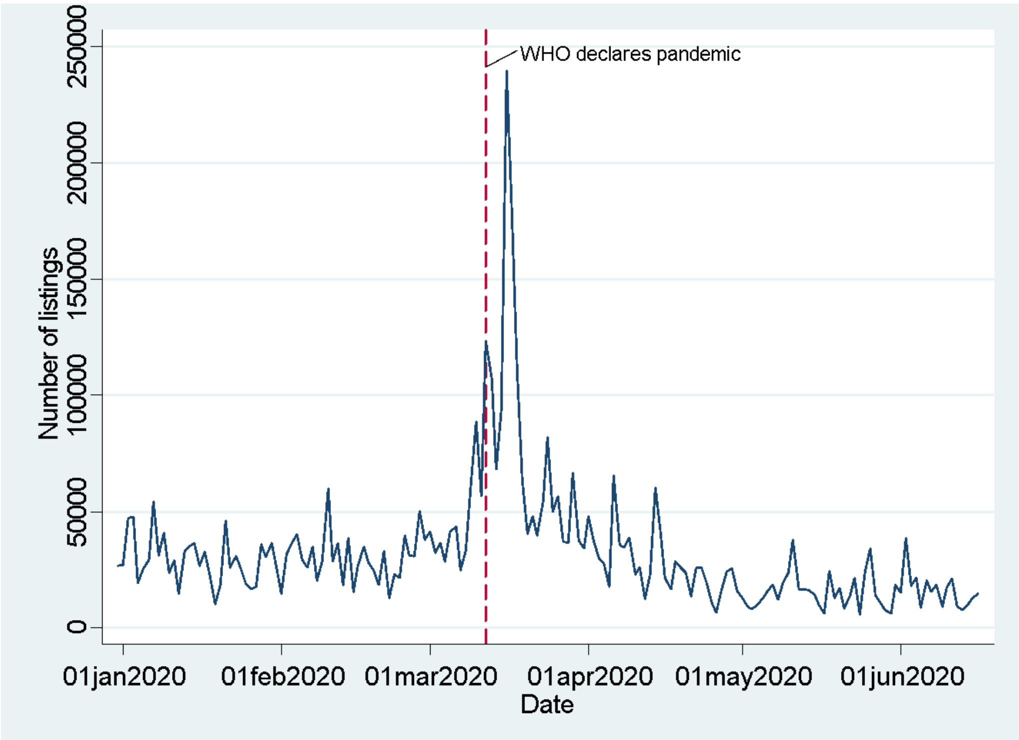

Figure 7.3: Daily number of listings in Bondora's Secondary Market (1 January 2020–30 June 2020)

Table 7.2 reports descriptive statistics for continuous variables used in the analysis of this Chapter. The statistics are reported in the breakdown of countries and total values for the data set. The mean value of RESULT_DUMMY for all database is 0.7850, indicating that around 78.5% of listings were successful. The success of the listings is similar across the three countries under consideration. The mean value of RESULT_DUMMY for individual countries varies between 0.7712 and 0.7893. The mean value for the loan status (STATUS_DUMMY) in the sample is 0.3941, indicating that 39.41% of listed loans are late loans. Status of loans considerably differs across the countries. The mean values of loan status are 0.3061 for Estonia, 0.5499 for Finland and 0.6073 for Spain, reflecting the variability of listed loans across the countries. Loan size (AMOUNT) and overdue days (LATEDAYS) also vary across the countries that indicate heterogeneity between the countries. The significant differences between the countries are addressed in the regression model by including the country-specific variable (POP) and running the regression on specific subsamples based on countries. The variables representing pandemic also vary during the period under consideration and across the three countries in the database.

Estonia and Finland recorded a relatively low number of COVID-19 cases. Mean value of recorded COVID-19 cases (CASES) are 16.39 for Estonia and 39.18 for Finland. Spain, on the other hand, recorded 1,742.08 cases on average during the period under consideration. The death numbers (DEATHS) also considerably differ between Spain and Estonia/Finland. The mean value of DEATHS for the whole database is 18.26 while for Spain, this number is considerably greater (166.68). Spain is also the country that experienced strictest of pandemic related restrictions represented by the Government response stringency index (COVID_INDEX). For Spain, COVID_INDEX is 52.10 on average (mean value), which is higher than the mean value for the whole database (39.84).

The average age of borrowers is higher for Finland (48 years) compared with the rest of the database (39 years for Estonia and 41 years for Spain). Borrowers from Spain are with higher DTI score (4.53 against 3.27 for the whole database), and consequently, incur higher interest rate (66.15% against 32.64% for the whole database) set by Bondora. However, loans issued in Spain are less likely to be restructured reflected in the variables of RESTRUCTURED_DUMMY. Loans issued in Spain are 19.53% likely to be restructured compared with the loans issued in Estonia (39.62%) and Finland (34.2%) rate riskier compared with the rest of the database.

There is a small variability in the duration of loans issued in different countries. Loans issued in Estonia have the duration of 45.97 months on average, while the durations of loans issued in Finland and Spain are 47.68 and 48.44 months respectively.

Table 7.2: Descriptive statistics for continuous variables

Variables	RESULT_ DUMMY	STATUS_ DUMMY	AMOUNT	LATEDAYS	PANDEMIC_ DUMMY	CASES	DEATHS	COVID_ INDEX	INDEX_ CHANGE
Estonia									
N	3579183	3579183	3579183	3579183	3579183	3579183	3579183	3576470	3579182
Mean	0.7893	0.3061	2941.7220	105.7240	0.5912	16.3925	0.3742	38.1793	-0.0000
Median	1	0	2232	0	1	5	0	44.4400	0
Standard deviation	0.4077	0.4609	2381.4840	255.4689	0.4916	23.1430	0.9404	30.6367	.0001
Finland									
N	1232422	1232422	1232422	1232422	1232422	1232422	1232422	1232349	1232422
Mean	0.7786	0.5499	3781.2980	214.7692	0.5650	39.1851	1.1892	38.9419	-.0057
Median	1	1	3720	4	1	19	0	50.9300	-.0020
Standard deviation	0.4151	0.4975	2296.6040	346.3618	0.4958	51.2078	3.7671	21.5310	.0289
Spain									
N	575323	575323	575323	575323	575323	575323	573144	575306	575323
Mean	0.7712	0.6073	2280.4010	261.2941	0.5297	1742.0790	166.6793	52.1015	-.0053
Median	1	1	2125	1	1	433	7	68.0600	.0002
Standard deviation	0.4200	0.4884	1508.2340	428.0265	0.4991	2420.3460	267.7094	32.5875	.0354
Total									
N	5386928	5386928	5386928	5386928	5386928	5386928	5384749	5384125	5386927
Mean	0.7850	0.3941	3063.1720	147.2862	0.5787	205.9101	18.2620	39.8415	-.0019
Median	1	0	2550	0	1	7	0	50	0
Standard deviation	0.4108	0.4887	2326.1720	306.5176	0.4938	953.3348	101.2723	29.3452	.0182

Table 7.2: Descriptive statistics for continuous variables (Contd.)

Variables	ESI	AGE	DTI	DISCOUNT RATE	INTEREST	RESTRUCTURED _DUMMY	PRINCIPAL _DIFF	LOAN DURATION
Estonia								
N	3048796	3579183	3579183	3579183	3579183	3579183	3578809	3579183
Mean	91.0013	40.2492	3.2429	-8.7628	24.0296	0.3962	0.8223	45.9775
Median	96.5000	39.0000	0.0000	-1.2500	22.7800	0.0000	0.0000	36.0000
Standard deviation	10.7664	12.0361	12.0683	65.9737	9.8817	0.4891	5.9435	13.3482
Finland								
N	1094930	1232422	1232422	1232422	1232422	1232422	1232112	1232422
Mean	88.3617	47.5366	2.7771	-10.9098	42.0182	0.3421	0.7223	47.6816
Median	90.4000	48.0000	0.0000	-8.4700	39.4900	0.0000	0.0000	48.0000
Standard deviation	8.6889	12.3510	11.1755	25.9940	15.3248	0.4744	6.3419	12.2259
Spain								
N	513235	575323	575323	575323	575323	575323	574898	575323
Mean	96.5407	41.7073	4.5269	-9.7113	66.1526	0.1953	0.8554	48.4455
Median	99.3000	41.0000	0.0000	-4.6200	59.3000	0.0000	0.0000	60.0000
Standard deviation	9.8592	10.7982	14.8324	111.2919	37.2735	0.3964	7.8059	12.9025
Total								
N	4656961	5386928	5386928	5386928	5386928	5386928	5385819	5386928
Mean	90.9912	42.0721	3.2735	-9.3553	32.6437	0.3624	0.8029	46.6310
Median	96.5000	41.0000	0.0000	-3.0000	29.2300	0.0000	0.0000	48.0000
Standard deviation	10.4580	12.3555	12.2091	66.1067	21.3615	0.4807	6.2594	13.0861

Table 7.3 reports the description of discrete variables used in the regression analysis of this chapter. Most borrowers in the database are male (66.48%), with the distribution of the ratings of borrowers is concentrated around the lower-rated loans. ‘A’ and ‘AA’ rated loans contribute to 4.51% and 5.42% of the total loan portfolio in Bondora’s Secondary Market during the period under consideration. At the same time, the largest share of listings (21.10%) is attributed to the loans rated as ‘E’. Borrowers are also more likely to be employed in their jobs for more than 5 years (39.67%) and have secondary education (38.46%). In terms of homeownership type, the largest category is the homeownership with 39.95% share, followed by the tenants in pre-furnished property with 21.98% share.

Table 7.3: Descriptive statistics for discrete variables used in Chapter 7

Variables	N	%
GENDER		
Male	3581050	66.48
Female	1486887	27.60
Other	318991	5.92
Total	5386928	100
RATING		
A	292102	5.42
AA	242747	4.51
B	688650	12.78
C	997536	18.52
D	1044084	19.38
E	1136671	21.10
F	747207	13.87
HR	237789	4.41
Total	5386786	100
EMPLOYMENT		
Trial period	15597	0.29
Up to 1 year	951367	17.66
Up to 2 years	118222	2.19
Up to 3 years	104802	1.95
Up to 4 years	69021	1.28
Up to 5 years	1384480	25.70
More than 5 years	2136681	39.67
Retiree	356635	6.62
Other	249248	4.63
Total	5386053	100
EDUCATION		
Primary education	608330	11.29
Basic education	136076	2.53
Vocational education	1198115	22.24
Secondary education	2071678	38.46
Higher education	1372579	25.48
Other	150	0.00
Total	5386928	100
HOMEOWNERSHIP		
Homeless	167	0.00
Owner	2152326	39.95
Living with parents	725052	13.46
Tenant, pre-furnished property	1184211	21.98
Tenant, unfurnished property	92868	1.72
Council house	54114	1.00
Joint tenant	30475	0.57
Joint ownership	70749	1.31
Mortgage	629047	11.68
Owner with encumbrance	17811	0.33
Other	430098	7.98
Total	5386918	100

Table 7.4 reports the descriptive statistics for selected variables before and during the pandemic. The mean value of RESULT_DUMMY considerably increased from 0.6881 to 0.8555 during the pandemic period. The standard deviation of RESULT_DUMMY decreased from 0.4632 to 0.3516 during the pandemic period compared with the pre-pandemic period. All three countries under consideration experienced similar changes in RESULT_DUMMY. The probability of listed loans being overdue (STATUS_DUMMY) decreased from 44.65% to 35.59% during the pandemic compared with pre-pandemic period (based on mean values). The standard deviation of STATUS_DUMMY decreased from 0.4971 to 0.4788 during the pandemic compared with the pre-pandemic period. This fall in the standard deviation was driven by the listings based on loans issued in Estonia. The standard deviation of STATUS_DUMMY for Estonia decreased from 0.4782 to 0.4456 during the pandemic compared with the pre-pandemic period. On the other hand, the same indicator increased from 0.4906 to 0.4998 for Finland and from 0.4768 to 0.4952 for Spain. The average loan size (AMOUNT) decreased during the pandemic compared with the pre-pandemic period, with the change being identical in all three countries. Overdue days (LATEDAYS) for listed loans also deceased during the pandemic compared with the pre-pandemic period in terms of both mean values and standard deviation. The two-sample t-test yielded significant values of chi-square statistics, as reported in Table 7.4. They indicate that there are significant differences between the pre- and post-pandemic values of dependent variables.

Table 7.4: Dependent variables before and after the pandemic

Table 7.4 reports the descriptive statistics for selected variables pre and post pandemic. Chi-square statistics are reported with *t* statistics in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$)

Variables	RESULT_DUMMY		STATUS_DUMMY		AMOUNT		LATEDAYS	
	Pre-pandemic	Post-pandemic	Pre-pandemic	Post-pandemic	Pre-pandemic	Post-pandemic	Pre-pandemic	Post-pandemic
Estonia								
N	1462995	2116188	1462995	2116188	1462995	2116188	1462995	2116188
Mean	0.7080	0.8456	0.3539	0.2732	3042.4230	2872.1040	124.2210	92.9364
Standard deviation	0.4547	0.3613	0.4782	0.4456	2427.8380	2346.3770	279.1638	236.8679
Chi-square statistic	-0.1380^{***} (-305.41)		0.0807^{***} (161.37)		170.3000^{***} (66.56)		31.2800^{***} (114.10)	
Finland								
N	536127	696295	536127	696295	536127	696295	536127	696295
Mean	0.6531	0.8753	0.5963	0.5141	3822.9120	3749.2570	240.2267	195.1677
Standard deviation	0.4760	0.3303	0.4906	0.4998	2333.1540	2267.5410	371.6851	324.1649
Chi-square statistic	-0.2220^{***} (-291.92)		0.0822^{***} (91.42)		73.6600^{***} (17.65)		45.0600^{***} (71.75)	
Spain								
N	270571	304752	270571	304752	270571	304752	270571	304752
Mean	0.6499	0.8789	0.6507	0.5688	2299.3790	2263.5520	296.9649	229.6241
Standard deviation	0.4770	0.3262	0.4768	0.4952	1539.5320	1479.6910	464.7936	389.7821
Chi-square statistic	-0.2290^{***} (-209.93)		0.0819^{***} (63.85)		35.8300^{***} (8.99)		67.3400^{***} (59.75)	
Total								
N	2269693	3117235	2269693	3117235	2269693	3117235	2269693	3117235
Mean	0.6881	0.8555	0.4465	0.3559	3138.2050	3008.5390	172.2157	129.1348
Standard deviation	0.4632	0.3516	0.4971	0.4788	2359.7290	2299.8920	336.2319	281.5404
Chi-square statistic	-0.167^{***} (-456.90)		0.0906^{***} (212.18)		129.7^{***} (63.91)		43.08^{***} (161.46)	

Table 7.5 reports a correlation matrix for the variables employed in the regression analysis of this chapter. Most of the variables are loosely correlated with each other reflected in low levels of Pearson’s correlation coefficients . High correlation coefficients are observed between the number of variables which are not used in the same model. For example, the correlation coefficient between CASES and DEATHS is 0.8920 indicating strong positive correlation. However, these two variables are used as the different proxies of the same indicator. The only concerning correlation observed in Table 7.5 is between COVID_INDEX and ESI. The high correlation level between these variables is predictable as government lockdowns surpass economic activity reflected in ESI. This chapter uses different combinations of variables and regression models. These diverse regression analyses generally expected to eliminate the problem of multicollinearity between these two variables.

Table 7.5: Correlation matrix

Table 7.5 reports Pearson's correlation coefficients between the variables employed in regression analyses of this chapter. Significant correlations in bold. See Table 7.1 for variable definitions.

	RESULT_ DUMMY	STATUS_ DUMMY	AMOUNT	LATEDAYS	PANDEMIC_ DUMMY	CASES	DEATHS	COVID_ INDEX
RESULT_DUMMY	1.0000							
STATUS_DUMMY	-0.1680	1.0000						
AMOUNT	-0.0483	0.0807	1.0000					
LATEDAYS	-0.1820	**0.5700**	0.1120	1.0000				
PANDEMIC_DUMMY	0.2010	-0.0916	-0.0275	-0.0694	1.0000			
CASES	0.0555	0.0612	-0.0650	0.0338	0.1760	1.0000		
DEATHS	0.0513	0.0513	-0.0590	0.0325	0.1530	**0.8920**	1.0000	
COVID_INDEX	-0.1300	0.0470	-0.0301	0.0792	**0.7130**	0.2510	0.2430	1.0000
INDEX_CHANGE	0.0167	-0.0346	-0.0110	-0.0167	0.0189	0.0407	0.0110	0.0258
ESI	-0.0689	0.0497	-0.0255	0.0322	-0.4610	-0.0196	-0.1080	**-0.5130**
RESTRUCTURED_DUMMY	-0.0123	-0.1200	0.0405	-0.1050	0.0094	-0.0624	-0.0554	-0.0200
AGE	0.0021	-0.0191	0.0514	-0.0441	0.0067	0.0030	0.0010	0.0058
GENDER	0.0252	-0.0201	-0.0262	-0.0225	-0.0079	0.2500	0.2270	0.0491
INTEREST	-0.0182	0.2510	-0.0377	0.2330	-0.0386	0.2800	0.2530	0.0813
LOANDURATION	-0.0085	0.0710	0.1970	0.0294	-0.0045	0.0298	0.0271	-0.0164
INCOMETOTAL	0.0006	0.0215	0.0495	0.0102	-0.0004	0.0030	0.0020	0.0045
RATING_	-0.0474	0.2820	0.0917	0.2210	-0.0403	0.2210	0.1980	0.0591
DEBTTOINCOME	-0.1300	0.1740	0.1920	0.4270	-0.0522	-0.0043	-0.0005	0.0120
DISCOUNTRATE	-0.0671	-0.0763	-0.0127	-0.0869	-0.0013	0.0042	0.0063	0.0217
PRINCIPAL_DIFF	-0.2080	-0.0369	-0.0143	0.0314	-0.0499	-0.0081	-0.0061	0.0265

Table 7.5: Correlation matrix (Contd.)

	INDEX_ CHANGE	ESI	RESTRUC TURED_ DUMMY	AGE	GENDER	INTEREST	LOAN DURATION	RATING_	DTI	DISCOUNT RATE
INDEX_CHANGE	-0.0657	1.0000								
ESI	0.0159	-0.0273	1.0000							
RESTRUCTURED_ DUMMY	-0.0319	-0.0304	-0.0123	1.0000						
AGE	-0.0355	0.0708	-0.0839	0.0232	1.0000					
GENDER	-0.0796	0.0608	-0.1530	-0.0377	0.2490	1.0000				
INTEREST	-0.0064	0.0026	-0.0707	-0.0407	0.0894	0.0600	1.0000			
LOANDURATION	-0.0165	-0.0180	-0.0184	0.0351	-0.0211	0.0429	-0.0060	1.0000		
RATING_	0.0060	0.0209	0.0708	-0.0328	0.1090	0.0104	0.0817	0.0500	1.0000	
DEBTTOINCOME	0.0020	-0.0197	-0.0008	0.0009	0.0162	-0.0069	-0.0114	-0.0152	-0.0415	1.0000
DISCOUNTRATE	0.0019	0.0177	-0.0385	-0.0098	-0.0029	-0.0076	-0.0328	-0.0050	0.0221	0.0228

7.6 Results of time series analysis with continuous dependent variable

The first stage of regression analysis estimates the following equation using a continuous dependent variable:

$$\gamma_t = \alpha + \delta\gamma_{t-1} + \beta_d D + \beta_E X_t^E + \varepsilon_{it} \quad [16]$$

γ_t – Dependent variable represented by the number of listings and probability of success at Bondora Secondary Market at time *t* (daily observations, continuous variable). Probability success of the listing at time *t* is calculated as:

$$Probablity\ of\ success_t = \frac{Number\ of\ successfull\ listings_t}{Number\ of\ listings_t} \quad [17]$$

γ_{t-1} – Number of listings (probability of success) at time *t-1* (lagged independent variable)

$\beta_d D$ – the variable representing the COVID-19 pandemic. Three proxies are used to represent the pandemic: (1) dummy variable equal to 1 for the dates later than 11 March[18] 2020 and 0 otherwise; (2) change in the number of country-level reported daily cases of COVID-19; (3) change in the number of country-level reported daily COVID-19 related deaths; (4) Government Response Stringency Index.

$\beta_E X_t^E$- vector of economy specific control variables (e.g., consumer confidence index)

The e_t is an error term that is unobserved factors. The β is the independent variable coefficient that reveals the magnitudes of independent variables effects on γ_t. The α is the intercept of the regression model.

Estimates are based on autoregressive conditional heteroskedasticity (ARCH) method of estimation. ARCH estimators fit regression models in which the volatility of a series varies through time. ARCH models estimate future volatility as a function of prior volatility by fitting models via conditional maximum likelihood (Bollerslev, Engle, & Nelson, 1994).

[18] The date on which the WHO declared COVID-19 to be a pandemic.

The results of the regression are reported in Table 7.6. The table uses the number of listings as the continuous dependent variable. The results indicate high and significant values of Wald chi-squared for three of the regression models. This indicates the fitness of the models and explains that there is a strong relationship between dependent variables and predictors. In terms of individual coefficients, pandemic dummy variable has a significant positive coefficient (0.5934). This indicates that the daily number of listings increased by 0.59% after the declaration of a pandemic by WHO. Based on the models (1) and (2), increase in the daily number of COVID-19 cases and deaths reduces the number of listings in the platform. However, the coefficients for these two variables are insignificant, preventing to draw a strong conclusion in this regard. Thus, the study moves into the analysis of time series data based on probability of success.

Table 7.6: COVID-19 and number of listings

Table 7.6 presents the results of time-series regression with a daily number of listings as the dependent variable. Refer to Table 7.1 for the variable description. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

	(1)	(2)	(3)
	DV=LISTINGS	**DV=LISTINGS**	**DV=LISTINGS**
PANDEMIC_DUMMY	0.5934***		
	(0.1149)		
CASES		-0.0115	
		(0.0575)	
DEATHS			-0.0208
			(0.0544)
INDEX_CHANGE	-1.7515***	-3.0934***	-3.0195***
	(0.2333)	(0.7493)	(0.5398)
ESI	0.0165***	0.0341***	0.0340***
	(0.0025)	(0.0045)	(0.0041)
AAR	-1.4522***	-2.2583	-2.0312
	(0.0419)	(5.1578)	(5.3835)
Wald chi2	2255.2733	198.0591	198.5992
Prob > chi2	0.0000	0.0000	0.0000
N	1629	1628	1628

Table 7.7 reports the results of the regression model that employs the probability of success as the dependent variable. Pandemic dummy significantly affects the daily probability of success of the listing in the Model (1) of Table 7.7. Probability of successfully listing of the loan stake by investors increases by 0.0548% during the pandemic period. Daily changes in the number of reported COVID-19 cases have a significant positive coefficient. So, a 1% increase in the number of cases is found to be leading to 0.0384% increase in the probability of success of the listing. The coefficient is found to be significant at more than 99% confidence level. On the contrary, the daily number of COVID-19 related deaths is found to be having a negative coefficient. The coefficient of this variable is -0.0322 with a confidence level of more than 99%. So, the number of COVID-19 related cases and deaths affect the probability of success in the opposite manner. The author believes that this effect is the result of deaths being the lagging indicator. Cases usually indicate early changes in the pandemic turmoil where investors are keen to cash-in and the true impact of the pandemic related disruptions did not hit the economy (Langreth, Court, & Cortez, 2020). This period is similar to the corporate bond market, where dealers absorb some of the ‘inventory’ during the selloff (Weill, 2007). However, as the pandemic progresses away from the early stage, withdrawals overweight the liquidity provided by the market participants. During March of 2020, a similar case was observed in the corporate bonds market, which faced withdrawals of almost US$ 100 billion (Scaggs, 2020). The number of COVID-19 related death numbers, lagging a couple of weeks behind the number of cases, represent this later period of the pandemic related market turmoil.

Other variables as it is reported in Table 7.6, and Table 7.7 are modestly performing in terms of significance levels. However, the results are largely undermined by the lack of borrower specific variables. Therefore, the next sections of this chapter explore the database of all the secondary market listing outcomes. This database consists of over 5 million observations consisting of both country and borrower specific variables. Several regression models in next sections use binary and continuous dependent variables.

Table 7.7: COVID-19 and probability of success

Table 7.7 presents the results of time-series regression with a probability of success as the dependent variable. Refer to Table 7.1 for the variable description. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

	(1)	(2)	(3)
	DV= PROB_SUCCESS	**DV= PROB_SUCCESS**	**DV= PROB_SUCCESS**
PANDEMIC_DUMMY	0.0548*		
	(0.0323)		
CASES		0.0384***	
		(0.0111)	
DEATHS			-0.0322**
			(0.0139)
INDEX_CHANGE	0.5291***	0.0642	-0.4398***
	(0.0761)	(0.1647)	(0.1397)
ESI	-0.0117***	0.0017	-0.0015*
	(0.0007)	(0.0010)	(0.0009)
AAR	-0.0128	-1.0654	-0.0436
	(0.0126)	(0.9056)	(0.9721)
LR chi2	574.0610	53.4208	52.7498
Prob > chi2	0.0000	0.0000	0.0000
N	1629.0000	1628.0000	1628.0000

7.7 Results of regression analysis with binary dependent variable

Empirical technique used in this section is the probit regression analysis, which estimates the dependent variable as binary values. This study performs a regression analysis employing the listings posted in Bondora over the period from January 2020 to June 2020. The model based on the binary dependent variable uses the same set of country-specific variables together with a wide range of borrower specific variables.

$$\gamma_t = \alpha + \beta_d D + \beta_E X_t^E + \beta_B X_t^B + \varepsilon_{it} \quad [18]$$

γ_t- Binary variable representing the status of listings or loans. Two proxies are used: (1) dummy variable representing the reason why the listing was sold or removed from the secondary market (1 - if the listing is 'successful' and 0 otherwise); (2) dummy variable representing the current status of the individual loan (1- if the loans is overdue and 0 otherwise).

$\beta_E X_t^E$- vector of borrower-specific control variables.

Other variables are defined as in equation [16]. This section uses the same data and the same explanatory variables, but different dependent variables. Table 7.8 provides the results of the regression models with the outcome of the listings as the dependent variable. The goodness of fit for the model (1) is 0.1490 represented by Pseudo R-squared value. Models (2-4) yield lower goodness of fit around 0.0711 and 0.0863. Likelihood Ratio (LR) chi-square values are significant indicating that at least one of the predictors' regression coefficient is not equal to zero.

The table reveals the significant impact of the pandemic on the outcome of listings. PANDEMIC_DUMMY, CASES and DEATHS are consistent across the models (1), (2) and (3). The coefficients for these variables are significantly positive. Specifically, a 1% increase in COVID-19 cases tends to increase the likelihood of successful listing by 0.0264%. The number of COVID-19 related deaths tend to have a greater impact on the likelihood of successful listing with a higher coefficient of 0.1896. On the other hand, pandemic related restrictions represented by COVID_INDEX have a negative impact on the likelihood of successful listing. A 1% increase in Government Response Stringency Index reduces the likelihood of successful listing by 0.2328%.

Country and borrower specific variables reported in Table 7.8 also yield some convincing results. Chapter 6 of this thesis explored the financial market indicators as determinants of credit risk in P2P lending market. This chapter explores the impact of stock market volatility on liquidity risk in P2P lending market. Using the findings reported in Table 7.8, this section of the thesis documents some important findings in terms of the impact of macroeconomic variables on the likelihood of successful listing. Coefficients for INDEX_CHANGE is significant and negative across the Models (1-4) reported in Table 7.8. Based on the coefficient values 1% increase in the daily change of the stock market leads to 0.0594–0.2200% decrease in the likelihood of successful listing. This chapter also extends the indicators of economic development with an Economic Sentiment Indicator (ESI) as a proxy. Coefficients for ESI are positive across the models (1-4) in Table 7.8 indicating that a 1% increase in ESI leads to around 0.1113–0.2098% increase in the likelihood of a successful listing. This section also employs a wide range of borrower specific variables which increase the credibility of the findings. Specifically, the debt-to-income ratio (DTI) is found to have significant positive coefficients and coefficients are consistent across the models (1-4) in Table 7.8. Coefficients for DISCOUNTRATE and PRINCIPAL_DIFF are significantly negative and consistent across the models (1-4) in Table 7.8 and vary between 0.2319 and 0.2944.

This study further conducts robustness tests by estimating the regression equation based on equation [18] on different subsamples of the database. Appendix C reports the results of these regression estimations (Tables C4 and C5). Generally, the results based on country subsamples are consistent with the results reported in Table 7.8. Whereas subsamples based on time periods based on each month from February to June of 2020 are inconsistent. These inconsistencies might reveal the different impact of the independent variables on the probability of successful listing at different stages of the pandemic. However, this aspect of the pandemic induced impact is considered to be out of the scope of this research and duly mentioned the last chapter of this thesis.

This study also empirically estimated STATUS_DUMMY, AMOUNT and LATE_DAYS. The results of regression estimations based on these three dependent variables are reported in Appendix C (Tables C1, C2 and C3). However, these estimations yielded inconsistent results across the models and deemed to be inferior in terms of their contribution to this research study. The author believes that these three variables are borrower specific, and current database does not fully reflect the level of borrower distress. Rather, the secondary market database reflects investor sentiment and aligns with the 4th research question of this study. As the COVID-19 related literature and data are at its infancy, this study does not go into further exploration of additional variables or subsets of the existing database. Rather, this chapter moves into an exploration of the probability of successful listing using survival analysis that is expected to further solidify the main findings of this chapter.

Table 7.8: COVID-19 and likelihood of successful listing

Table 7.8 presents the results of probit regression analysis for the likelihood of successful listings (RESULT_DUMMY). Number of listings analysed: 5,386,928. Failed: 1,158,162 (21.50%). Successful: 4,228,766 (78.50%). Refer to Table 7.1 for the variable description. All model specifications employ robust standard errors in parentheses (* *p*<0.10, ** *p*<0.05, *** *p*<0.01).

	(1)	(2)	(3)	(4)
	DV= RESULT_ DUMMY	**DV= RESULT_ DUMMY**	**DV= RESULT_ DUMMY**	**DV= RESULT_ DUMMY**
PANDEMIC_DUMMY	1.0089*** (0.0056)			
CASES		0.0264*** (0.0029)		
DEATHS			0.1896*** (0.0037)	
COVID_INDEX				-0.2328*** (0.0063)
INDEX_CHANGE	-0.0757*** (0.0020)	-0.1126*** (0.0049)	-0.0594*** (0.0050)	-0.2200*** (0.0028)
ESI	0.2098*** (0.0198)	0.1113*** (0.0264)	0.1584*** (0.0344)	0.1470*** (0.0175)
POP	-0.0030 (0.0029)	-0.1227*** (0.0075)	-0.5002*** (0.0099)	0.0174*** (0.0039)
RESTRUCTURED	0.0137*** (0.0041)	-0.0985*** (0.0077)	-0.1105*** (0.0078)	-0.0445*** (0.0057)
AGE	0.0003* (0.0002)	-0.0009** (0.0004)	-0.0010*** (0.0004)	-0.0006** (0.0003)
GENDER	0.0667*** (0.0027)	0.0072 (0.0044)	0.0046 (0.0044)	0.0278*** (0.0036)
INTEREST	0.0757*** (0.0083)	-0.0555*** (0.0155)	-0.0291* (0.0157)	0.0100 (0.0120)
LOANDURATION	0.0030*** (0.0002)	-0.0008*** (0.0003)	-0.0004 (0.0003)	-0.0000 (0.0002)
DTI	0.0081*** (0.0003)	0.0068*** (0.0005)	0.0066*** (0.0005)	0.0075*** (0.0004)
DISCOUNTRATE	-0.0017*** (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)	-0.0002*** (0.0000)
PRINCIPAL_DIFF	-0.0556*** (0.0006)	-0.0599*** (0.0010)	-0.0595*** (0.0010)	-0.0640*** (0.0008)
RATING				
A	0.2934*** (0.0401)	-0.0352 (0.1297)	-0.0348 (0.1311)	0.1052* (0.0620)
B	0.0498 (0.0320)	-0.6220*** (0.1019)	-0.6468*** (0.1030)	-0.1796*** (0.0503)
C	0.0758*** (0.0290)	-0.5071*** (0.0972)	-0.5575*** (0.0983)	-0.1355*** (0.0459)
D	0.0007 (0.0288)	-0.4865*** (0.0968)	-0.5515*** (0.0979)	-0.1624*** (0.0458)
E	0.1082*** (0.0292)	-0.4927*** (0.0973)	-0.5604*** (0.0984)	-0.1489*** (0.0464)
F	-0.1413*** (0.0303)	-0.5551*** (0.0986)	-0.6311*** (0.0997)	-0.2665*** (0.0480)
HR	0.0063 (0.0320)	-0.1492 (0.1007)	-0.2362** (0.1018)	0.1160** (0.0503)
EMP_DUR				
Trial period	-0.0333*** (0.0085)	0.0241 (0.0157)	0.0215 (0.0158)	-0.0273** (0.0114)

Table 7.8: COVID-19 and likelihood of successful listing (Contd.)

Up to 1 year	-0.0381***	0.0473**	0.0542***	-0.0308**
	(0.0099)	(0.0189)	(0.0190)	(0.0133)
Up to 2 year	0.1306***	0.2507**	0.2581***	0.2073***
	(0.0440)	(0.0982)	(0.0989)	(0.0677)
Up to 3 year	-0.0197**	0.0383**	0.0383**	-0.0270**
	(0.0095)	(0.0176)	(0.0178)	(0.0128)
Up to 4 year	-0.0089	0.2229***	0.2260***	0.0915***
	(0.0156)	(0.0314)	(0.0317)	(0.0233)
Up to 5 year	0.0464***	0.2207***	0.2234***	0.1950***
	(0.0174)	(0.0348)	(0.0351)	(0.0262)
More than 5 years	-0.0592***	0.0940***	0.0895**	-0.0283
	(0.0180)	(0.0354)	(0.0356)	(0.0261)
Retiree	-0.0055	0.0266	0.0258	-0.0118
	(0.0091)	(0.0167)	(0.0168)	(0.0122)
EDUCATION				
Primary education	0.1886	-0.0260**	-0.0257**	0.0053
	(0.4083)	(0.0121)	(0.0122)	(0.0089)
Basic education	0.1351	0.0641**	0.0626**	0.0262
	(0.4085)	(0.0285)	(0.0287)	(0.0207)
Vocational education	0.1890	0.0729***	0.0729***	0.0545***
	(0.4083)	(0.0102)	(0.0103)	(0.0070)
Secondary education	0.1360	-0.0508***	-0.0516***	-0.0348***
	(0.4083)	(0.0085)	(0.0086)	(0.0067)
Higher education	0.1648	0.0000	0.0000	0.0000
	(0.4083)	(.)	(.)	(.)
HOMEOWNERSHIP				
Owner	0.1517	-0.0025	-0.0026	0.0223**
	(0.3850)	(0.0139)	(0.0140)	(0.0104)
Living with parents	0.1074	-0.0340**	-0.0304**	-0.0127
	(0.3850)	(0.0151)	(0.0153)	(0.0121)
Tenant, pre-furnished property	0.1341	0.0379***	0.0394***	0.0262**
	(0.3850)	(0.0138)	(0.0139)	(0.0103)
Tenant, unfurnished property	-0.0037	-0.1820***	-0.1759***	-0.1696***
	(0.3851)	(0.0252)	(0.0253)	(0.0188)
Council house	0.0766	-0.0138	-0.0293	0.0177
	(0.3855)	(0.0391)	(0.0392)	(0.0291)
Joint tenant	0.1333	0.1638***	0.1566***	0.0702*
	(0.3857)	(0.0515)	(0.0518)	(0.0376)
Joint ownership	0.1057	0.0642	0.0990**	0.0292
	(0.3856)	(0.0447)	(0.0455)	(0.0332)
Mortgage	0.1432	0.0324**	0.0291**	0.0188*
	(0.3850)	(0.0147)	(0.0148)	(0.0111)
Owner with encumbrance	0.2068	-0.0947	-0.0889	0.1016*
	(0.3867)	(0.0689)	(0.0692)	(0.0558)
LR chi2	107598.9390	12917.1587	15661.3616	26627.1128
Prob > chi2	0.0000	0.0000	0.0000	0.0000
Pseudo-R-squared	0.1490	0.0711	0.0863	0.0777
N	5386928.0000	5386928.0000	5386928.0000	5386928.0000

7.8 Results of survival analysis

The next empirical technique of this chapter is survival analysis, which facilitates estimating not only whether but also when the event occurs (Royston & Lambert, 2011). This study performs a survival regression analysis employing the listings posted in Bondora over the period from January 2020 to June 2020. The model, based on survival analysis, uses the same set of country-specific variables together with a wide range of borrower specific variables as follows:

$$\gamma_t = \alpha + \beta_d D + \beta_E X_t^E + \beta_B X_t^B + \varepsilon_{it} \qquad [19]$$

$\beta_E X_t^E$ - vector of borrower specific control variables.

Other variables are defined as in equation [16]. Both techniques use the same data and the same explanatory variables, but the dependent variable differs. In equation [16], the dependent variable is a continuous variable, while in the survival analysis based on equation [19] the dependent variable is the time until the occurrence of an event of interest. The event of interest is an unsuccessful listing where investors cannot sell their stake in the loan. In the case of this research, the dependent variable is the risk of failure or how long the listing survived until the failure. This is done by means of Cox regression, which relates survival time and explanatory variables.

Table 7.9 provides the survival analysis results, by means of Cox regressions, one for each explanatory variable. Table 7.9 provides the regression coefficients, standard errors, risk ratios and significance of p-values. The regression coefficient is interpreted as a k-fold increase in risk. Hence, a negative regression coefficient for an explanatory variable means that the risk is lower. Risk ratio can be interpreted as the predicted change in the risk for a unit increase in the explanatory variable. The table reveals important practical findings. All of the pandemic variables are consistent across the models. The goodness of fit for three models indicates the fit of the model around 0.03 and 0.0399 represented by Pseudo R-squared values. Also evident from the Likelihood Ratio (LR) chi-square values that at least one of the predictors' regression coefficient is not equal to zero.

If coefficients are considered, the variable dummy of the pandemic has a significant negative coefficient. This negative coefficient for the variable is largely counter-intuitive. It indicates a lower risk of failed listing for the period after the declaration of the pandemic. The Model (1) estimates that after the declaration of the pandemic expected to log of the hazard ratio decreased by -1.9793 holding all other predictors constant. The same result obtained from the other variables representing the impact of the pandemic. Both COVID-19 related deaths and cases have negative coefficients. Each percentage increase in the number of reported daily COVD-19 cases reduces the risk by 0.6854 times, ‘ceteris paribus’ (Model (2)). By contrast, the risk of unsuccessful listing reduces 0.7503 times under each percentage increase in reported daily COVD-19 related deaths. The significance test for the coefficient tests the null hypothesis that it equals zero. In all three indicators of pandemic statistically, significant differences have been found ($p<0.000$). Results are coherent, to a certain degree, with the first stage of regression analysis of this chapter with continues dependent variable.

Another important aspect of survival analysis is the survival curves that indicate the probabilities of failure at a certain point of time (Figure 7.4). The chart in Figure 7.4 displays the survival curves for each period under consideration, before and after the pandemic. It can be clearly appreciated that the probability of survival is higher during the pandemic period than before the pandemic.

Table 7.9: COVID-19 and survival time of secondary market listing

Table 7.9 presents the results of Cox regression analysis for survival time of listings. Refer to Table 7.1 for the variable description. Number of listings analysed: 5,386,928. Failed: 1,158,162 (21.50%). Successful: 4,228,766 (78.50%). All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, ***p<0.01).

	(1)		(2)		(3)		(4)	
	DV=SURVIVAL_TIME		DV=SURVIVAL_TIME		DV=SURVIVAL_TIME		DV=SURVIVAL_TIME	
	Parameter estimate	**Hazard ratio**	**Parameter estimate**	**Hazard ratio**	**Parameter estimate**	**Hazard ratio**	**Parameter estimate**	**Hazard ratio**
PANDEMIC_DUMMY	-1.9793*** (0.0072)	0.1382*** (0.0010)						
CASES			-0.3778*** (0.0011)	0.6854*** (0.0008)				
DEATHS					-0.2873*** (0.0019)	0.7503*** (0.0015)		
COVID_INDEX							-2.1609*** (0.0176)	0.1152*** (0.0020)
INDEX_CHANGE	0.3192*** (0.0080)	5.1679*** (1.2703)	0.9745*** (0.0048)	7.6430*** (1.9731)	0.1360*** (0.0041)	4.4742*** (1.8638)	-0.3794*** (0.0051)	0.6843*** (0.0035)
ESI	0.0093*** (0.0004)	1.0094*** (0.0004)	0.0080*** (0.0003)	1.0080*** (0.0003)	0.0549*** (0.0003)	1.0564*** (0.0004)	1.1805*** (0.0427)	3.2561*** (0.1390)
POP	-0.1046*** (0.0029)	0.9007*** (0.0026)	0.2222*** (0.0030)	1.2489*** (0.0038)	-0.0964*** (0.0032)	0.9081*** (0.0029)	0.0972*** (0.0079)	1.1021*** (0.0087)
RESTRUCTURED	0.1680*** (0.0040)	1.1830*** (0.0048)	0.1520*** (0.0040)	1.1642*** (0.0047)	0.1472*** (0.0040)	1.1586*** (0.0047)	0.2058*** (0.0105)	1.2285*** (0.0130)
AGE	0.0010*** (0.0002)	1.0010*** (0.0002)	0.0008*** (0.0002)	1.0008*** (0.0002)	0.0010*** (0.0002)	1.0010*** (0.0002)	0.0025*** (0.0005)	1.0025*** (0.0005)
GENDER	0.0425*** (0.0026)	1.0434*** (0.0027)	0.0535*** (0.0026)	1.0549*** (0.0028)	0.0305*** (0.0026)	1.0310*** (0.0027)	0.0778*** (0.0066)	1.0810*** (0.0071)
INTEREST	-0.0003*** (0.0001)	0.9997*** (0.0001)	-0.0008*** (0.0001)	0.9992*** (0.0001)	-0.0003*** (0.0001)	0.9997*** (0.0001)	-0.2095*** (0.0225)	0.8110*** (0.0183)
LOANDURATION	0.0015*** (0.0001)	1.0015*** (0.0001)	0.0030*** (0.0001)	1.0030*** (0.0001)	0.0006*** (0.0001)	1.0006*** (0.0001)	0.0017*** (0.0004)	1.0017*** (0.0004)
INCOMETOTAL	-0.0001** (0.0000)	0.9999** (0.0000)	-0.0001*** (0.0000)	0.9999*** (0.0000)	-0.0002*** (0.0000)	0.9998*** (0.0000)	0.0023*** (0.0006)	1.0023*** (0.0006)

Table 7.9: COVID-19 and survival time of secondary market listing (Contd.)

DTI	0.0038***	1.0038***	0.0028***	1.0028***	0.0026***	1.0026***	0.0002***	1.0002***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0000)	(0.0000)
DISCOUNTRATE	0.0002***	1.0002***	0.0002***	1.0002***	0.0002***	1.0002***	0.0123***	1.0124***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0003)
PRINCIPAL_DIFF	0.0160***	1.0162***	0.0154***	1.0155***	0.0146***	1.0147***	-0.0265	0.9739
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.1384)	(0.1348)
RATING								
A	0.1823***	1.2000***	0.1357***	1.1453***	0.0847**	1.0884**	0.6644***	1.9432***
	(0.0392)	(0.0470)	(0.0392)	(0.0449)	(0.0392)	(0.0426)	(0.1090)	(0.2119)
B	0.2693***	1.3090***	0.2292***	1.2576***	0.1819***	1.1995***	0.9127***	2.4910***
	(0.0305)	(0.0400)	(0.0305)	(0.0384)	(0.0305)	(0.0366)	(0.1036)	(0.2582)
C	0.4104***	1.5074***	0.3655***	1.4412***	0.2784***	1.3210***	1.0261***	2.7903***
	(0.0280)	(0.0422)	(0.0280)	(0.0404)	(0.0280)	(0.0370)	(0.1036)	(0.2889)
D	0.4973***	1.6443***	0.4575***	1.5801***	0.3807***	1.4633***	1.0889***	2.9710***
	(0.0276)	(0.0453)	(0.0275)	(0.0435)	(0.0275)	(0.0403)	(0.1044)	(0.3102)
E	0.5871***	1.7987***	0.4993***	1.6475***	0.3787***	1.4604***	0.8168***	2.2632***
	(0.0273)	(0.0491)	(0.0273)	(0.0450)	(0.0273)	(0.0399)	(0.1070)	(0.2421)
F	0.3470***	1.4148***	0.3014***	1.3518***	0.2406***	1.2721***	0.5992***	1.8206***
	(0.0275)	(0.0388)	(0.0274)	(0.0371)	(0.0274)	(0.0349)	(0.1103)	(0.2008)
HR	0.3486***	1.4171***	0.1884***	1.2073***	0.1832***	1.2010***	0.0242	1.0245
	(0.0283)	(0.0401)	(0.0283)	(0.0342)	(0.0283)	(0.0340)	(0.0213)	(0.0218)
EMP_DUR								
Trial period	-0.0629*	0.9390*	-0.0281	0.9723	-0.0021	0.9979	-0.0413	0.9595
	(0.0340)	(0.0320)	(0.0340)	(0.0331)	(0.0340)	(0.0340)	(0.0253)	(0.0243)
Up to 1 year	-0.0399***	0.9609***	-0.0241***	0.9762***	-0.0028	0.9972	-0.1566	0.8550
	(0.0093)	(0.0090)	(0.0093)	(0.0091)	(0.0093)	(0.0093)	(0.1258)	(0.1076)
Up to 2 year	-0.0393***	0.9615***	-0.0429***	0.9580***	0.0119	1.0119	0.0024	1.0024
	(0.0134)	(0.0129)	(0.0134)	(0.0128)	(0.0134)	(0.0136)	(0.0239)	(0.0239)
Up to 3 year	-0.1693***	0.8443***	-0.1485***	0.8620***	-0.0966***	0.9079***	-0.1557***	0.8558***
	(0.0148)	(0.0125)	(0.0148)	(0.0127)	(0.0148)	(0.0134)	(0.0417)	(0.0357)
Up to 4 year	0.0283*	1.0287*	0.0264*	1.0268*	0.0657***	1.0679***	-0.3091***	0.7341***
	(0.0151)	(0.0155)	(0.0151)	(0.0155)	(0.0151)	(0.0161)	(0.0476)	(0.0350)
Up to 5 year	-0.0295***	0.9710***	-0.0216**	0.9786**	0.0014	1.0014	0.1513***	1.1633***
	(0.0089)	(0.0087)	(0.0089)	(0.0087)	(0.0089)	(0.0090)	(0.0437)	(0.0508)
More than 5 years	-0.0168**	0.9834**	-0.0147*	0.9854*	0.0193**	1.0194**	0.0008	1.0008
	(0.0084)	(0.0082)	(0.0084)	(0.0083)	(0.0084)	(0.0086)	(0.0227)	(0.0227)

Table 7.9: COVID-19 and survival time of secondary market listing (Contd.)

Retiree	-0.0882***	0.9156***	-0.0736***	0.9291***	-0.0495***	0.9517***	0.9443***	0.2964
	(0.0099)	(0.0091)	(0.0099)	(0.0092)	(0.0099)	(0.0095)	(0.0367)	(0.2940)
EDUCATION								
Primary education	-0.1635	0.8492	-0.1410	0.8685	-0.3525	0.7029	-0.0891***	1.3333***
	(0.2953)	(0.2508)	(0.2935)	(0.2549)	(0.2941)	(0.2067)	(0.0106)	(0.0436)
Basic education	-0.1835	0.8323	-0.1277	0.8801	-0.3323	0.7173	-0.1085***	1.5265***
	(0.2955)	(0.2459)	(0.2936)	(0.2584)	(0.2942)	(0.2110)	(0.0134)	(0.0658)
Vocational education	-0.1516	0.8594	-0.1352	0.8735	-0.3422	0.7102	-0.1163***	1.2198***
	(0.2953)	(0.2538)	(0.2935)	(0.2564)	(0.2941)	(0.2088)	(0.0114)	(0.0453)
Secondary education	-0.1302	0.8780	-0.0813	0.9219	-0.2964	0.7435	0.1598***	1.1550***
	(0.2953)	(0.2592)	(0.2934)	(0.2705)	(0.2940)	(0.2186)	(0.0147)	(0.0530)
Higher education	-0.1120	0.8941	-0.0910	0.9130	-0.2881	0.7497	0.1758***	0.9952
	(0.2953)	(0.2640)	(0.2935)	(0.2679)	(0.2940)	(0.2204)	(0.0389)	(0.1245)
HOMEOWNERSHIP								
Owner	0.2807	1.3241	0.2529	1.2878	0.2251	1.2525	0.0728***	1.0755***
	(0.2509)	(0.3322)	(0.2493)	(0.3211)	(0.2498)	(0.3129)	(0.0106)	(0.0114)
Living with parents	0.2328	1.2621	0.2103	1.2340	0.1941	1.2142	0.0855***	1.0893***
	(0.2509)	(0.3167)	(0.2494)	(0.3077)	(0.2499)	(0.3034)	(0.0135)	(0.0147)
Tenant, pre-furnished property	0.2105	1.2343	0.1878	1.2066	0.1624	1.1764	0.0197*	1.0199*
	(0.2509)	(0.3097)	(0.2493)	(0.3008)	(0.2498)	(0.2939)	(0.0115)	(0.0117)
Tenant, unfurnished property	0.2798	1.3228	0.2905	1.3370	0.2833	1.3275	0.0085	1.0085
	(0.2510)	(0.3321)	(0.2494)	(0.3335)	(0.2499)	(0.3318)	(0.0147)	(0.0148)
Council house	0.1472	1.1585	0.1427	1.1534	0.1566	1.1695	-0.0216	0.9786
	(0.2514)	(0.2912)	(0.2498)	(0.2882)	(0.2503)	(0.2928)	(0.0381)	
Joint tenant	0.2039	1.2262	0.2230	1.2498	0.2271	1.2550	-0.1082***	0.8975***
	(0.2515)	(0.3084)	(0.2500)	(0.3124)	(0.2505)	(0.3143)	(0.0106)	(0.0095)
Joint ownership	0.1481	1.1597	0.1405	1.1509	0.1287	1.1373	-0.0867***	0.9170***
	(0.2515)	(0.2916)	(0.2499)	(0.2876)	(0.2504)	(0.2848)	(0.0134)	(0.0123)
Mortgage	0.2425	1.2744	0.2345	1.2643	0.2191	1.2450	-0.1736***	0.8407***
	(0.2509)	(0.3198)	(0.2493)	(0.3152)	(0.2498)	(0.3110)	(0.0114)	(0.0096)
Owner with encumbrance	0.2329	1.2623	0.1756	1.1919	0.1983	1.2194	-0.1683***	0.8451***
	(0.2528)	(0.3191)	(0.2513)	(0.2995)	(0.2518)	(0.3070)	(0.0147)	(0.0124)
LR chi2	248201.1066		271000.4306		164087.4244		28884.4414	
Prob > chi2	0.0000		0.0000		0.0000		0.0000	
Pseudo-R-squared	0.0300		0.0328		0.0399		0.0276	
N	5386928.0000		5386928.0000		5386928.0000		5386928.0000	

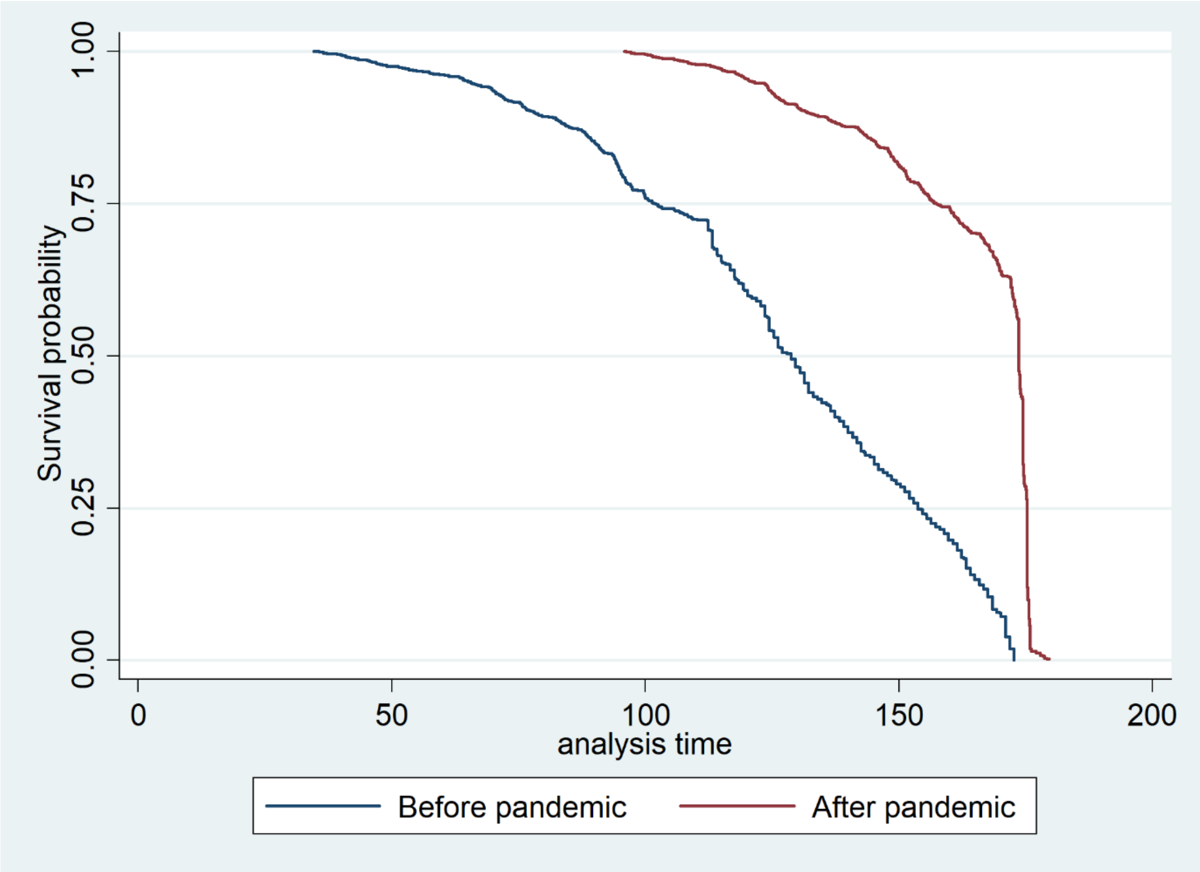

Figure 7.4: Survival function before and during the pandemic

7.9 Results of LASSO selection method

This study recognizes that there are some limitations under the probit regression approach due to its high dimensionality. Many explanatory and control variables can be prone to multicollinearity problem and potentially blur the results. The rationale behind the inclusion of borrower and country-specific control variables are provided in section 4.7.3 with relevant references to existing literature. Nevertheless, the issue related to a large number of variables has been raised as a potential cause of concern in big data analysis (Cox & Battey, 2017; Cox, Kartsonaki & Keogh, 2018). To further strengthen the regression model, this study implements the type of machine learning process, known as the least absolute shrinkage and selection operator (LASSO). This method provides more robust analysis that allows finding the important variables in a large set of potential determinants (Tibshirani, 1996; Belloni et al. 2016). The method shrinks regression coefficients by penalizing their magnitude and provides a narrow set of important variables, making the results easier to interpret and resolving the problem of multicollinearity (Meinshausen and Yu, 2009).

Using the LASSO selection method, this study selects a set of variables that may be more important in determining the listing probability of success in Bondora secondary market. The selected variables and coefficients are reported in Table 7.10. Few of the 40 variables used in original probit regression (reported in Table 7.8) are omitted in LASSO selection. Omitted variables are reported as empty cells in Table 7.10. All of the proxies for COVID-19 risk have similar coefficients. Most of the explanatory variables also hold their respective coefficient signs in LASSO selection model. Therefore, this study can conclude that the selection of variables is well justified and does not significantly affect the impact of COVID-19 variables.

Table 7.10: COVID-19 and likelihood of successful listing (LASSO selection)

Table 7.8 presents the results of LASSO regression for the likelihood of successful listings (RESULT_DUMMY). Number of listings analysed: 5,386,928. Failed: 1,158,162 (21.50%). Successful: 4,228,766 (78.50%). Refer to Table 7.1 for the variable description. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

	(1)	(2)	(3)	(4)
	DV= RESULT_ DUMMY	**DV= RESULT_ DUMMY**	**DV= RESULT_ DUMMY**	**DV= RESULT_ DUMMY**
PANDEMIC_DUMMY	0.1461			
CASES		0.0288		
DEATHS			0.0236	
COVID_INDEX				-0.0155
INDEX_CHANGE	-0.0040	-0.0165	-0.0153	-0.0116
ESI	-0.3031	-0.2905	-0.2570	-0.2522
POP	0.0049	-0.0318	-0.0221	-0.0004
RESTRUCTURED	x	-0.0162	-0.0168	-0.0082
AGE	-0.0002	-0.0002	-0.0001	-0.0002
GENDER	0.0238	0.0030	0.0028	0.0142
INTEREST	0.0386	0.0042	0.0016	0.0090
LOANDURATION	0.0003	-0.0003	-0.0003	-0.0003
DTI	0.0013	0.0011	0.0011	0.0012
DISCOUNTRATE	-0.0004	-0.0001	-0.0001	-0.0002
PRINCIPAL_DIFF	-0.0124	-0.0117	-0.0117	-0.0132
RATING				
A	0.0892	0.0426	0.0413	0.0247
B	0.1187	0.0552	0.0550	0.0432
C	0.0587	0.0023	0.0014	0.0053
D	0.0370	x	x	0.0023
E	x	-0.0367	-0.0375	-0.0266
F	-0.0463	-0.0344	-0.0309	-0.0523
HR	-0.0344	0.0211	0.0241	x
EMP_DUR				
Trial period	-0.0069	-0.0067	-0.0089	-0.0070
Up to 1 year	-0.0025	0.0092	0.0098	-0.0010
Up to 2 year	-0.0305	-0.0112	-0.0130	-0.0277
Up to 3 year	-0.0092	-0.0034	-0.0055	-0.0082
Up to 4 year	-0.0013	0.0275	0.0244	0.0080
Up to 5 year	-0.0145	-0.0099	-0.0130	-0.0122
More than 5 years	-0.0095	-0.0069	-0.0097	-0.0104
Retiree	-0.0057	-0.0033	-0.0055	-0.0062
EDUCATION				
Primary education	-0.0447	-0.0609	-0.0571	-0.0363
Basic education	0.0132	0.0081	0.0093	0.0058
Vocational education	-0.0145	-0.0114	-0.0106	-0.0113
Secondary education	0.0112	0.0210	0.0240	0.0104
Higher education	-0.0012	-0.0109	-0.0112	-0.0046
HOMEOWNERSHIP				
Owner	-0.0171	0.0127	x	0.0651
Living with parents	x	x	x	x
Tenant, pre-furnished property	0.0044	x	x	0.0032
Tenant, unfurnished property	-0.0062	-0.0110	-0.0117	-0.0073
Council house	-0.0080	-0.0123	-0.0130	-0.0125
Joint tenant	0.0094	0.0329	0.0333	0.0122
Joint ownership	-0.0202	-0.0260	-0.0254	-0.0207
Mortgage	-0.0006	-0.0043	-0.0040	-0.0051
Owner with encumbrance	0.0138	-0.0142	-0.0141	0.0143
N	5386928.0000	5386928.0000	5386928.0000	5386928.0000

7.10 Discussion and concluding remarks

This chapter discussed the implication of COVID-19 on the P2P lending market liquidity using the listings database of Bondora's Secondary Market. To sum the finding of this chapter, loan defaults and number of listing in Bondora's Secondary Market considerably increased after the declaration of the pandemic by the World Health Organization (WHO). This was confirmed in both graphical descriptive analysis and regression models. This impact is explained by the surge in selling pressure and inventory accumulation by investors. This behaviour is typical during the pandemic when the market turmoil triggers so-called 'dash for cash' when investors run to liquidity (Gros, 2020). During this period, investors tend to sell risky assets (e.g. their stake in P2P lending loans) for cash and purchases of less risky assets (Wójcik & Ioannou, 2020). This finding falls in line with the early studies of Leoni, (2013); Lagoarde-Segot and Leoni, (2013); Skoufias, (2003). It also falls in line with the latest literature on the impact of the COVID-19 pandemic on liquidity provision in the financial markets (Haddad, Moreira, & Muir, 2020; Kargar et al., 2020; O'Hara & Zhou, 2020).

On the contrary, the findings of this chapter indicated that the probability of successfully listing a loan stake increased during the pandemic period. Specifically, when the author employed survival analysis technique the risk of unsuccessful listing reduced as the reported daily COVD-19 related deaths and cases increased. This result contradicts the latest studies of the impact of COVID-19 pandemic on the financial sector such as Baig, Butt, Haroon and Rizvi (2020). Results of Baig et al. (2020) suggest that increases in COVD-19 related deaths and cases are associated with a significant increase in market illiquidity and volatility. However, the findings of this chapter should be perceived with caution and not conceived as a strong indication of certain tendencies in the market. Rather, this chapter just scratches the surface of the topic and opens broad room for further research. Thus, it is important to highlight a number of remarks related to the limitations of the current chapter and room for further research.

First, most of the impact of the pandemic on the financial sector, as well as to P2P lending market has not yet been realised. For instance, a spike in withdrawals mainly occurred during the March of 2020 in Bondora P2P lending platform. While by April 2020, cash withdrawals mostly dropped to pre-crisis levels (Bondora, 2020). However, throughout March and June of 2020, loan applications largely surpassed available investments. Bondora also limited the loan originators, set partial payout feature, and most of the EU countries placed moratoriums on loan repayments. Thus, the findings of this chapter are largely distorted by various restrictions superimposed by third parties rather than defined by the market.

Second, as the current COVID-19 pandemic related crisis progresses into the later stage, liquidity problems experienced by households, businesses, and public sector organisations might also transfer into a more severe stage. Issues related to liquidity might lead to a chain reaction of non-performing loans, insolvencies and bankruptcies, sending the global economy into a vortex of financial and economic crises. P2P lending as one of the risky sectors of financing might experience a wave of defaults in late 2020 and during 2021. This stream of defaults tends to seriously test the resilience of the industry and force platforms to reconsider their risk management models. Currently, most of the P2P platforms are revising their main tool of security against the financial hardship, 'provision fund'. P2P lending platforms now withholding up to 50% of investor interest income as a contribution to 'provisional fund' (RateSetter, 2020). This type of extreme measures might be useful to solve short-term liquidity problems but drives away yield-hungry investors in the long-term.

Third, the transformation of the financial sector that started after the GFC of 2007–2008 is expected to accelerate after the pandemic. The pandemic could help the transformation of 'shadow banking' (banking by non-banks) with an extensive emphasis on alternative lending practices (Sindreu, 2020). P2P lending market as one of the prominent facets of alternative lending might transform into the mainstream from its niche position currently held.

To sum, as the COVID-19 pandemic affected financial markets, there is a need for better understanding of the dynamics of successful P2P lending under the conditions of financial distress. By extending the modelling and findings of the current chapter, subsequent studies can concentrate on the dynamics of defaults in P2P lending under financial distress. Moreover, by concentrating on both liquidity and default risk, subsequent studies can improve current risk management models used by P2P lending platforms. P2P lending platforms, on its turn, can improve their security mechanisms, such as contributions to provisional funds. In this regard, further studies can be enhanced with the models of diversification for P2P lending, just like in traditional finance, by paving the way for future best practices in the market.

Chapter 8:

Conclusion

8.1 Introduction

This thesis examined regional, country and borrower-specific determinants of default among P2P lending loans. It put a specific emphasis on determining the impact of inflation and interest rate on the credit risk of the platform. Credit risk has been proxied by borrower defaults throughout the regression models of this study. This thesis reviewed literature related to P2P lending and traditional finance for building the background of the empirical model. An empirical model was applied in the context of USA data set based on state-level data (Chapter 5). Chapter 6 provided an empirical model in the context of Continental Europe data set based on country-level data. Both empirical analyses in Chapters 5 and 6 explored the credit risk among P2P lending platforms. Then the empirical modelling was applied to Continental Europe data set with the purpose of exploring the liquidity risk among P2P lending platforms (Chapter 7).

The literature on the topic is very limited and did not provide convincing evidence to support the findings of the study. Instead, this study relied on the triangulation method in empirical analyses for enhancing the credibility of the findings. The results from baseline regression analysis were reported in conjunction with robustness tests. Moreover, the findings of empirical analysis in Chapter 5 were cross-examined in the empirical analysis of Chapter 6. In this regard, this study provided convincing evidence in terms of the main research questions highlighted in Chapter 1. This last chapter of the thesis provides concluding remarks with regards to this research project. This chapter follows with the section summarising this thesis with an emphasis on findings and their compliance with earlier research. Then it follows with the implications of this study in policymaking, investing practices and academic theory. Finally, this chapter concludes with the limitations of this study and room for further research.

8.2 Summary of chapters

8.2.1 Interest rate and credit risk

Conceptual framework (section 1.6) based on the theory of asymmetric information identifies that the average interest rate affects credit risk via determining the probability of default. The hypothesis developed in section 3.5 highlights the strong theoretical evidence that a hike in interest rate increases the probability of default. However, empirical evidence is mixed in both traditional finance and P2P lending. Therefore, Chapters 5 and 6 intend to analyse the impact of interest rate on the probability of default. Chapter 5 analyses the impact of interest rate on the probability of default in the context of regional data based on LendingClub (USA). The probability of default is estimated employing a number of borrower-specific, regional and macroeconomic variables as baseline regression model according to section 4.6.3. Furthermore, the findings from the baseline regression model are tested via endogeneity correction and robustness tests with subsamples of the data set. Therefore, the findings of Chapter 5 and 6 are robust despite of the limited underlying literature and deficiencies in the data.

The findings consistently provide evidence that interest rate significantly and positively affects the probability of default. This implies that the higher interest rates for loans link to higher delinquency rates, causing more borrowers to miss payments on their outstanding loans. Thus, under higher interest rate environment investors into P2P lending have to hedge against higher credit risk. The findings remain robust even after controlling for endogeneity and robustness tests. The findings also hold with both regional (USA) and country-level (Continental Europe) inflation data. This result falls in line with the only available study in P2P lending (Serrano-Cinca et al., 2015) and the range of empirical studies in traditional financial markets (Espinoza and Prasad, 2010; and Beck et al., 2000). However, no prior study investigated the regional or country-level interest rate in P2P lending market. This study also serves as a comprehensive investigation of whether the reaction of delinquencies to changes in interest rate depends on borrower ratings, religiosity and loan volume issued in the region/country. Overall, the results in this study solidified the evidence that higher interest rate significantly increases the probability of default, and consequently, credit risk in P2P lending market.

8.2.2 Inflation and credit risk

The impact of inflation on credit risk has not yet been analysed in the context of P2P lending. Thus, this study is unique in terms of exploring the relationship between inflation and credit risk in P2P lending market. However, this topic has been analysed in financial literature from both theoretical and empirical perspective. Most of the existing literature view inflation as a source of erosion in real income, and thus, ultimately leading to a deterioration of loan portfolio quality. However, empirical evidence appears to be mixed among traditional financial markets with an ambiguous relationship observed between inflation and delinquencies (Chopin & Zhong, 2001; Ghosh, 2015; Klein, 2013). In view of the existing evidence from traditional finance, this study develops a conceptual framework with inflation as one of the determinants of credit risk in P2P lending market (section 1.6). Section 4.6, then develops a regression model with the probability of default as the dependent variable and inflation as one of the explanatory variables. This baseline regression model is empirically estimated in Chapters 5 with regional inflation and in Chapter 6 with country-level inflation rates. Chapters 5 and 6 also use instrumental variable estimation for endogeneity correction and robustness tests.

The impact of inflation is found to be positive in the baseline models across Chapters 5 and 6. This finding proves to be robust to endogeneity correction with instrumental variables. This result is also consistent with theoretical evidence and existing empirical studies on commercial banks (Klein, 2013; Skarica, 2014; Ghosh, 2015). Therefore, this thesis solidified the prevalent theoretical understandings in financial literature with regards to inflation within the context of P2P lending. In this regard, the probability of default tends to increase under the high inflation rate environment in the P2P lending market.

8.2.3 Regional- and country-level determinants of credit risk

The conceptual framework developed in Chapter 1 highlights the model that uses a wide range of regional and country-specific factors as determinants of credit risk. The use of these determinants in line with a range of borrower-specific characteristics is the unique aspect of this study. Empirical analyses in Chapters 5 and 6 used specific indicators representing the macroeconomic environment and business sentiment.

These indicators were used as independent variables in regression models and revealed several important relationships.

Economic growth represented by GDP growth is found to have a positive but insignificant impact on borrower delinquencies. This finding is documented in Chapter 5 within the context of the USA and in Chapter 6 within the context of Continental Europe. However, this study revealed the importance of another variable which is related to economic development. Chapter 5 documented that an increase in established new businesses increased the probability of default within the context of the USA. This finding highlights the specific character of P2P lending industry that reflects more on new and small businesses, rather than the overall state of the economy.

Chapter 6 used two variables, namely NPL and INDEX, to explore the interaction between the traditional financial markets and P2P lending market. The findings indicate that the stock market development (INDEX) decreases delinquency rates among P2P lending loans. On its turn, NPLs have a positive relationship with the delinquency rates, which means that an increase in NPLs leads to higher delinquencies in P2P lending market. These findings have important repercussions for the industry in understanding the interaction between P2P lending traditional financial markets. However, the impact of INDEX and NPL requires further robustness tests and opens wide room for further research. The room for further research is discussed in section 8.5.

This study is also unique in terms of providing evidence that inflation has a significantly different relationship with delinquency rates based on the degree of religiosity. Inflation has a significant negative impact on bad loans among high religious states and countries. On the contrary, the impact is significantly positive among low religious states and countries. Prior literature related to traditional finance linked religious adherence to lower risk-taking and lower involvement in questionable activities (Hilary & Hui, 2009; Callen & Fang, 2015). However, existing literature did not explore religious adherence in terms of the functional form relating inflation to probability of default. In this regard, this study is not only relevant for P2P lending but also to traditional financial markets.

8.2.4 Pandemic and liquidity risk

Chapter 7 is reflected from the changes in the business environment as a result of global COVID-19 pandemic. Chapter 7 empirically examines liquidity risk incurred by P2P lending market during the COVID-19 pandemic using the data set consisting of secondary market listings at Bondora (Estonia) P2P lending platform. Prior studies on P2P lending or crowdfunding did not examine the issues related to liquidity risk and behaviour of investors under the adverse economic conditions. This study uses time series and survival regression analyses in Chapter 7. The findings of Chapter 7 provide early evidence of the pandemic induced exposure to liquidity risk in P2P lending market. In Chapter 7, this study used the daily number of listings and the probability of successful selling in Bondora’s Secondary Market as continuous dependent variables. The findings indicate that the secondary market listings substantially increased around the early days of the pandemic. Furthermore, Chapter 7 analyses the potential impact of COVID-19 on P2P lending industry using the method of survival analysis. The findings from survival analysis indicate that despite increased volatility, the probability of success increased during the period of the pandemic. However, it should be noted that the findings of Chapter 7 should be used with caution because of the limitations imposed by third parties and rapid changes happening in the industry. The limitations of the current study are further discussed in section 8.4 of this chapter.

8.3 Contributions of the study

As it is highlighted earlier in this thesis, existing studies are very limited in terms of empirical investigation for observing particular factors influencing credit and liquidity risk in P2P lending. For instance, there is no understanding of the dynamics of successful P2P lending or the use and distribution of P2P lending mechanisms. Moreover, scholars did not search for existing contradictions or similarities between traditional theories of finance and P2P lending mechanisms. Therefore, this study is reflected in an urgent need for empirical investigation of the risks faced by P2P lending. This study contributes to the literature in several ways by using a broad range of factors and with proper reference to existing theoretical understandings. Accordingly, this study makes a decent contribution in terms of theory, methodology and policy implications.

First, this study allows quantifying risks and analysing risk factors related to business cycles in P2P lending market. Thus, it fills the gap in the existing literature by developing a cross country model that is tested via econometric analysis. This thesis proposes suggestions for platform management in overcoming or controlling various risk factors in P2P lending market with consideration of regional and country-specific factors. Econometric models estimated in Chapters 5, 6 and 7 serve as a framework of risk management in P2P lending platforms. These models with their consideration of beyond borrower-specific factors, allow for comprehensive estimation of credits risk, setting of borrower ratings, informing investors about potential risk level and setting up the 'provision fund'.

Second, this research highlights a number of policy implications based on the findings by identifying the potential of the development of P2P lending market in particular countries. Specifically, this study highlights the relationship between the P2P lending and traditional financial markets. It identifies that stock market development (INDEX) decreases delinquency rates among P2P lending loans. This study also documents that higher bank sector NPLs leads to higher delinquencies in P2P lending market. Based on these identified risk factors, recommendations can be made for governments that allow exploiting the existing potential of an industry. In this regard, countries with less developed financial markets can create favourable business and regulatory environments to serve the underserved in the financial market. More regulations and privileges could be introduced that may enhance the efficiency of the market.

Third, as the P2P lending has been developing on its own without any effect coming from the economy, evidence on the relationship between economic variables and P2P lending will prove vital for further development of this industry. In this respect, based on the same evidence, forecasting mechanisms may be put in place for mitigating risk factors in a way that were not possible before. For instance, the sensitivity of credit risk to external factors is reflected in variable coefficients (e.g. coefficients for inflation and consumer confidence) in regression analyses. Moreover, findings of Chapter 7 highlight the sensitivity of liquidity risk to the changes in a pandemic or its severity (reflected in the number of reported cases and deaths). These coefficients may be used for stress testing of P2P lending portfolio under certain conditions such as an increase in inflation or decrease in consumer confidence.

Fourth, the findings of this research significantly contribute to investors' understanding of P2P lending and allow realistically manage expectations. Current risk assessment of loans in P2P lending mostly relies on borrower-specific characteristics and assumes that loan diversification cancels out the majority of the inherent risks. However, this study reveals the degree of individual specificity and heterogeneity of loan portfolios based in different regions and countries. This research highlights that regional and country characteristics are important determinants of solvency and competitiveness in P2P lending. This level of heterogeneity with its own specificity can be considered in investment policy, loan assessment and setting interest rates by P2P lending platforms.

Fifth, this research makes a significant contribution to the theory in terms of the application of conventional theories in P2P lending market. The theory related to information asymmetry has been extensively tested in traditional finance. This study developed a conceptual framework based on asymmetric information and tested this theory in a different setting of P2P lending market. Using asymmetric information theory in a different context, thus widens its scope and improves applicability.

To sum, by concentrating on both liquidity and default risk, this study can improve current risk management models and security mechanisms used by P2P lending platforms. In comparison, the subsequent theoretical outcome of this study is the models of regional and cross-country diversification for P2P lending, just like in traditional finance. These models are also expected to contribute to future best practices and sufficient growth of the market. However, this research has some limitations that hinder some of the findings but open the wide room for further research.

8.4 Limitations of the study

This thesis has some limitations based on the inherent deficiencies of the data and the limited scope of this research. First, the findings of empirical chapters are based on a relatively small sample. The main reason for this limitation is the availability of the data. P2P lending industry does not publicly report detailed statistics about the loans issued by the platforms. This study only used the loan-books of three P2P lending platforms. However, empirical analyses used most of the publicly available data and covered a substantial part of the P2P lending market in the USA and Continental Europe. Second, this study uses continuous dependent variables in most of the empirical analyses involving regression models. This study falls short of employing alternative models like logistics regression or survival analysis for the estimation of credit risk in Chapters 5 and 6. This limitation of the study is mainly reflected from the limited scope of this thesis. Third, this study has limited geographical scope only considering the USA and Continental Europe. In this regard, countries with developed P2P lending markets such as the UK and China are not analysed in this study. This limitation is caused by both data availability and research strategy. As the data for P2P lending industry in different countries do not share common characteristics, this study estimated regression models within the context of case studies for the USA and Continental Europe separately. Fourth, this study did not test the robustness of the findings other than the interest rate and inflation. This is mainly reflected from the fact that further exploration of these factors is out of the scope of this study. Fifth, this study has limited scope related to the impact of COVID-19 pandemic on P2P lending market. For instance, this study did not analyse the impact of the pandemic on delinquencies and consequently, credit risk. In fact, the real impact of the pandemic to credit risk can only be observed by 2021. By this time, it is expected that various government-imposed restrictions are lifted, and liquidity problems are transferred into insolvency. Finally, the data used in this study comes from various sources. The author put considerable effort to prepare a single unified database by collecting information from different sources. Therefore, this study has certain limitations of self-reported data. Accordingly, some aspects of the study related to empirical modelling and literature review could be enhanced.

8.5 Room for further research

This study also opens several avenues for extending the current research work. Existing studies in P2P lending such as the work of Cumming (2020); Dushnitsky et al. (2016) and Wei and Lin (2016) highlighted certain areas of research for further research. Based on the suggestions of earlier studies and findings of the current study, the author suggests a number of directions for upcoming studies on this topic. In this respect, further studies can extend the modelling and findings of the current study to widen the scope of research into the number of prospective areas. First, this study does not have information about the amount of capital collected over the years by the platforms in the sample database. Adding such time-variant information would be interesting. Currently, some platforms publicly disclose this information. However, further studies are required to invest a substantial amount of resources in collecting and aggregating publicly disclosed information into the single database. Second, the data set used in Chapters 5 ends at 2018, while in Chapter 6 it ends at 2019, thus embracing a period in which the USA and European P2P lending industry was far from maturity. Repeating this exercise in five years would better assess the industry dynamics—accounting, for instance, for the possible impact of the pandemic induced recession. Third, this thesis studied the credit and liquidity risk incurred by P2P lending. Future work that would explore the economic performance of P2P lending platforms with specific emphasis on profitability would be of interest for both policymakers and platforms. Future studies could also explore how this performance depends on the country where the platforms are located. Fourth, inter-platform competitions are also considered to be an interesting area of future empirical research. Along these same lines, comparisons could be made as to the performance of P2P lending and other forms of alternative lending practices. Finally, further studies can concentrate on the dynamics of defaults in P2P lending under financial distress. Chapter 7 of this thesis explored the liquidity risk of P2P lending platforms under current adverse economic conditions. Future studies can explore the default risk incurred by platforms when the market data becomes available.

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Appendices

Appendix A: List of Publications

Book Chapter

Nigmonov A., Daradkeh H., From One Crisis to Another: Impact of Covid-19 Pandemic on Peer-to-Peer Lending Market. In: Boubaker, S., and Nguyen, D. K. (eds), Financial Transformations beyond the Covid-19 Health Crisis, World Scientific Publishing, 2020 [Status: publication by November 2020]. Link: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3738075

Journal Article Submission

Nigmonov A., Shams, S.M.M., Alam, K., Born in Crisis: Early Impact of COVID-19 Pandemic on P2P Lending Market. Journal of Business Finance and Accounting [Status: submitted for review].

Conference Papers

Nigmonov A., Shams, S.M.M., Alam, K., Macroeconomic Determinants of Loan Delinquencies: Evidence from US Peer-to-Peer Lending Market, 2020 Asian Development Bank- Asian Bureau of Finance and Economic Research Specialty Conference 'Fintech to Enable Development, Investment, Financial Inclusion, and Sustainability', Singapore (Virtual) 22-24 September 2020 [Status: accepted as working paper]. Link: http://abfer.org/media//abfer-events-2020/specialty-conf/other-papers/Other-Papers-not-presented.pdf

Nigmonov A., Shams, S.M.M., Alam, K., Macroeconomic Determinants of Loan Delinquencies: Evidence from US Peer-to-Peer Lending Market, 33rd Australasian Finance and Banking Conference. University of New South Wales, Sydney (Virtual). 15–17 December 2020 [Status: presentated at the conference]. Link: https://www.business.unsw.edu.au/about/schools/banking-finance/seminars-conferences/australasian-finance-banking-conference

Nigmonov A., Determinants of Default under Financial Distress in European P2P Lending Market. Submitted to 4th European Alternative Finance Research Conference, Utrecht University (Virtual), 6 October 2020 [Status: presented at the conference]. Link: https://www.uu.nl/sites/default/files/European%20Alternative%20Finance%20Research%20Conference%202020%20programsept2020.pdf

Appendix B: Results of additional regression analyses (Chapter 5)

Table B1: Impact of average interest rate on bad loans (baseline regression results)

Table B1 reports the results for the Random Effects panel data estimation representing the effect of platform specific variable (average interest rate) on bad loans with control variables. Results are divided into 2 panels. Panel A uses total dollar value of bad loans as dependent variable. Panel B employs the number of bad loans as dependent variable. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

Panel A. Dollar value of bad loans as dependent variable

	Model 1	**Model 2**	**Model 3**	**Model 4**
Variables	**DV= BADLOANSVOL**	**DV= BADLOANSVOL**	**DV= BADLOANSVOL**	**DV= BADLOANSVOL**
AVEINTRATE	0.6049***	0.6621***	0.6522***	0.7943***
	(0.0380)	(0.0835)	(0.0908)	(0.0441)
LOANVOLUME	0.2014***	0.2007***	0.1989***	0.1701***
	(0.0458)	(0.0467)	(0.0467)	(0.0491)
AVEDTI	0.3961***	0.4832***	0.4535***	0.4668***
	(0.0474)	(0.0963)	(0.0535)	(0.0263)
INTUSERS	0.0914***	0.0961***	0.0962***	0.0970***
	(0.0083)	(0.0085)	(0.0079)	(0.0091)
GDP_CONT	-0.0971*	-0.1087*	-0.1078**	-0.1204**
	(0.0564)	(0.0558)	(0.0548)	(0.0611)
AVEINCOME	0.4441***	0.6735***	0.6802***	0.7067***
	(0.0984)	(0.0480)	(0.0625)	(0.0452)
NEW_BUS		0.2692	0.2557	0.3617
		(0.4000)	(0.4292)	(0.4166)
REPUBLICAN			0.2358**	0.2451**
			(0.1148)	(0.1060)
LABOR_FORCE				-0.0002
				(0.2079)
Constant, Yr. & Ind. Effects	Yes	Yes	Yes	Yes
Overall R-squared	0.4390	0.4470	0.4494	0.4613
N	3223 (Bootstrap sampling)	3121 (Bootstrap sampling)	3121 (Bootstrap sampling)	2855 (Bootstrap sampling)

Table B1 (Contd.)

Panel B. Number of bad loans as dependent variable

	Model 1	Model 2	Model 3	Model 4
Variables	**DV= BADLOANSCOUNT**	**DV= BADLOANSCOUNT**	**DV= BADLOANSCOUNT**	**DV= BADLOANSCOUNT**
AVEINTRATE	1.5108**	1.7133***	1.7513***	1.3686**
	(0.5983)	(0.6154)	(0.6167)	(0.6298)
LOANVOLUME	0.0490	0.0396	0.0405	0.0682
	(0.0504)	(0.0505)	(0.0505)	(0.0523)
AVEDTI	0.2465*	0.2434*	0.2529*	0.3091**
	(0.1430)	(0.1427)	(0.1430)	(0.1492)
INTUSERS	-0.0177***	-0.0185***	-0.0189***	-0.0174***
	(0.0047)	(0.0048)	(0.0048)	(0.0049)
GDP_CONT	-0.1650***	-0.1590***	-0.1598***	-0.1428***
	(0.0233)	(0.0235)	(0.0235)	(0.0244)
AVEINCOME	0.1727**	0.2011	0.1983	0.1322
	(0.0813)	(0.1737)	(0.1739)	(0.1773)
NEW_BUS		-0.1507	-0.1362	-0.1510
		(0.1773)	(0.1775)	(0.1880)
REPUBLICAN			-0.1849**	-0.0807
			(0.0766)	(0.0805)
LABOR_FORCE				0.0364
				(0.0843)
Constant, Yr. & Ind. Effects	Yes	Yes	Yes	Yes
Overall R-squared	0.4262	0.4242	0.4251	0.4199
N	3223 (Bootstrap sampling)	3121 (Bootstrap sampling)	3121 (Bootstrap sampling)	2855 (Bootstrap sampling)

Table B2: Impact of inflation on bad loans (baseline regression results)

Table B2 reports the results for the Random Effects panel data estimation representing the effect of inflation on bad loans with control variables. Results are divided into 2 panels. Panel A uses total dollar value of bad loans as dependent variable. Panel B employs the number of bad loans as dependent variable. All model specifications employ robust standard errors in parentheses (* *p*<0.10, ** *p*<0.05, *** *p*<0.01).

Panel A. Dollar value of bad loans as dependent variable				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Variables	**DV= BADLOANSVOL**	**DV= BADLOANSVOL**	**DV= BADLOANSVOL**	**DV= BADLOANSVOL**
INFLATION	0.3856***	0.2918*	0.2959*	0.3393**
	(0.1476)	(0.1554)	(0.1647)	(0.1701)
LOANVOLUME	0.2342***	0.2310***	0.2290***	0.2035***
	(0.0452)	(0.0461)	(0.0461)	(0.0484)
AVEDTI	2.6161***	2.7010***	2.6685***	2.6927***
	(0.3536)	(0.4335)	(0.3617)	(0.4486)
INTUSERS	0.0932***	0.0978***	0.0980***	0.0991***
	(0.0077)	(0.0084)	(0.0082)	(0.0097)
GDP_CONT	-0.0985**	-0.1091*	-0.1082*	-0.1196*
	(0.0475)	(0.0582)	(0.0631)	(0.0631)
AVEINCOME	1.4338***	1.6505***	1.6576***	1.6810***
	(0.1108)	(0.1353)	(0.1569)	(0.1447)
NEW_BUS		0.2434	0.2291	0.3369
		(0.3428)	(0.3855)	(0.4927)
REPUBLICAN			0.2496**	0.2503**
			(0.1004)	(0.0989)
LABOR_FORCE				0.0280
				(0.1867)
Constant, Yr. & Ind. effects	Yes	Yes	Yes	Yes
Overall R-squared	0.4504	0.4538	0.4563	0.4696
N	3227 (Bootstrap sampling)	3124 (Bootstrap sampling)	3124 (Bootstrap sampling)	2858 (Bootstrap sampling)

Table B2 (Contd.)

Panel B. Number of bad loans as dependent variable				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Variables	**DV= BADLOANSCOUNT**	**DV= BADLOANSCOUNT**	**DV= BADLOANSCOUNT**	**DV= BADLOANSCOUNT**
INFLATION	0.1806**	0.1637*	0.1656*	0.2730***
	(0.0874)	(0.0899)	(0.0899)	(0.0973)
LOANVOLUME	0.0255	0.0151	0.0163	0.0432
	(0.0495)	(0.0496)	(0.0496)	(0.0513)
AVEDTI	0.2198	0.2176	0.2283	0.2845*
	(0.1432)	(0.1431)	(0.1434)	(0.1495)
INTUSERS	-0.0177***	-0.0186***	-0.0189***	-0.0173***
	(0.0047)	(0.0048)	(0.0048)	(0.0049)
GDP_CONT	-0.1666***	-0.1607***	-0.1616***	-0.1456***
	(0.0232)	(0.0234)	(0.0234)	(0.0243)
AVEINCOME	0.1726**	0.1965	0.1937	0.1204
	(0.0812)	(0.1735)	(0.1738)	(0.1772)
NEW_BUS		-0.1644	-0.1496	-0.1678
		(0.1773)	(0.1776)	(0.1882)
REPUBLICAN			-0.1881**	-0.0851
			(0.0766)	(0.0805)
LABOR_FORCE				0.0386
				(0.0842)
Constant, Yr. & Ind. effects	Yes	Yes	Yes	Yes
Overall R-squared	0.3868	0.1901	0.1931	0.3114
N	3227 (Bootstrap sampling)	3124 (Bootstrap sampling)	3124 (Bootstrap sampling)	2858 (Bootstrap sampling)

Table B3: Impacts of average interest rate and inflation on bad loans (two-stage GMM regression with instrumental variables)

Table B3 presents the two stage GMM regression results with instrumental variables for of average interest rate and inflation. Panel A sample takes dollar value of bad loans as dependent variable. Panel B sample takes the number of bad loans as dependent variable. All model specifications employ robust standard errors in parentheses (* *p*<0.10, ** *p*<0.05, *** *p*<0.01)

Panel A. Dollar value of bad loans as dependent variable

	Model 1: Average interest rate and bad loans		**Model 2: Inflation and bad loans**	
	1st Stage	2nd Stage	1st Stage	2nd Stage
	DV= AVEINTRATE	**DV= BADLOANSVOL**	**DV= AVEINTRATE**	**DV= BADLOANSVOL**
AVEINRATE/INFLATION		0.80522** (0.36811)		0.7434*** (0.2047)
UNEM_RATE	-0.0308*** (0.0035)			
EARNINGS			-0.1200*** (0.0363)	
MUNI_M			0.1502*** (0.0181)	
FEDFUNDS	-0.3379*** (0.0179)	0.0136*** (0.0007)	0.0095 (0.0085)	-0.0005 (0.0020)
LOANVOLUME	-0.2303** (0.1136)	-0.0367*** (0.0042)	0.8684*** (0.0976)	0.0899*** (0.0238)
AVEDTI	0.0000 (0.0038)	-0.0001 (0.0001)	-0.0045 (0.0030)	-0.0021*** (0.0007)
INTUSERS	0.0220 (0.0198)	0.0062*** (0.0007)	-0.0973*** (0.0153)	-0.0079** (0.0037)
GDP_CONT	-0.0756 (0.1062)	0.0067* (0.0038)	6.4686*** (1.2460)	-0.2728 (0.3092)
AVEINCOME	0.3891** (0.1529)	-0.0459*** (0.0055)	0.1660 (0.1165)	0.0682** (0.0278)
NEW_BUS	0.0919 (0.0646)	0.0023 (0.0023)	0.2022*** (0.0508)	0.0363*** (0.0123)
REPUBLICAN	-0.0833 (0.0614)	-0.0061*** (0.0022)	0.2415*** (0.0515)	-0.1009*** (0.0119)
Constant, Yr. & Ind. effects	Yes	Yes	Yes	Yes
R-squared		0.2625		0.1718
N	1000 (Bootstrap sampling)	1000 (Bootstrap sampling)	1000 (Bootstrap sampling)	1000 (Bootstrap sampling)
Instrument diagnostics tests:				
Test of endogeneity: GMM distance test statistic of endogeneity		3.3976*		5.9574**
Underidentification test: (Kleibergen-Paap rk LM statistic)		1080.2191***		1519.2465***
Weak identification test: (Cragg-Donald Wald F statistic)		691.3008		548.9059
Overidentification test: Sargan (1958) $\chi 2$ [*p*-value]		0.5480 [0.4591]		0.6882 [0.8760]

Table B3 (Contd.)

Panel B. Number of bad loans as dependent variable

	Model 1: Average interest rate and bad loans		Model 2: Inflation and bad loans	
	1st Stage	2nd Stage	1st Stage	2nd Stage
	DV= INFLATION	DV= BADLOANSCOUNT	DV= INFLATION	DV= BADLOANSCOUNT
AVEINRATE/ INFLATION		1.8223***		
		(0.1255)		
UNEM_RATE	-0.0234***			
	(0.0023)			
EARNINGS	-0.0839***			
	(0.0031)			
MUNI_M				-0.0600***
				(0.0009)
FEDFUNDS			-0.0186***	
			(0.0059)	
LOANVOLUME			0.2740***	
			(0.0047)	
AVEDTI	-0.1211***	-0.0043*	0.0359***	0.0136***
	(0.0140)	(0.0024)	(0.0091)	(0.0007)
INTUSERS	1.5886***	0.0141	0.5150***	-0.0367***
	(0.0897)	(0.0148)	(0.0694)	(0.0042)
GDP_CONT	0.0026	0.0004	0.0005	-0.0001
	(0.0024)	(0.0005)	(0.0026)	(0.0001)
AVEINCOME	-0.0834***	-0.0084***	-0.0869***	0.0062***
	(0.0126)	(0.0026)	(0.0133)	(0.0007)
NEW_BUS	-0.0867***	0.0307**	0.0002	0.0067*
	(0.0208)	(0.0141)	(0.0215)	(0.0038)
REPUBLICAN	0.0179	0.0155	0.1012	-0.0144
	(0.6276)	(0.269)	(0.6911)	(0.0206)
Constant, Yr. & Ind. effects	Yes	Yes	Yes	Yes
Wald chi2		577.55***		201.57***
N	1000 (Bootstrap sampling)	1000 (Bootstrap sampling)	1000 (Bootstrap sampling)	1000 (Bootstrap sampling)
Instrument diagnostics tests:				
Test of endogeneity: GMM distance test statistic of endogeneity		3.3518*		7.2611**
Underidentification test: (Kleibergen-Paap rk LM statistic)		723.8657***		2683.0681***
Weak identification test: (Cragg-Donald Wald F statistic)		385.4251		1738.3954
Overidentification test: Sargan (1958) $\chi 2$ [*p*-value]		0.7125 [0.4201]		0.3951 [0.8760]

Table B4: Impacts of loan volume and average interest rate on bad loans (baseline regression for two subsamples based on aggregate loan volumes)

Table B4 presents the baseline regression results for two subsamples. Subsamples are based on the criteria of loan volumes in states being higher or lower than median level. All model specifications employ robust standard errors in parentheses (* *p*<0.10, ** *p*<0.05, *** *p*<0.01)

Panel A. Dollar value of bad loans as dependent variable

	Lower than median loan volume	**Higher than median loan volume**	**Lower than median loan volume**	**Higher than median loan volume**
Variables	**DV = BADLOANSVOL**	**DV = BADLOANSVOL**	**DV = BADLOANSVOL**	**DV = BADLOANSVOL**
AVEINTRATE			0.7657***	-0.8024***
			(0.0437)	(0.0676)
INFLATION	0.1031	0.1616*		
	(0.1208)	(0.0860)		
LOANVOLUME	-0.0498**	-0.0860***	-0.0859***	-0.1098***
	(0.0246)	(0.0137)	(0.0151)	(0.0142)
AVEDTI	0.1403***	0.1609***	0.1609***	0.16086***
	(0.0090)	(0.0120)	(0.0129)	(0.0114)
INTUSERS	0.0696***	0.0653***	0.0653***	0.0659***
	(0.0092)	(0.0104)	(0.0108)	(0.0117)
GDP_CONT	0.0624***	0.0448***	0.0732**	0.0466***
	(0.0229)	(0.0119)	(0.0312)	(0.0123)
AVEINCOME	0.0744	0.0565	0.0141	0.0257
	(0.0909)	(0.0645)	(0.0256)	(0.0557)
NEW_BUS	-0.0498**	-0.0860***	-0.0859***	-0.1098***
	(0.0246)	(0.0137)	(0.0151)	(0.0142)
REPUBLICAN	-0.4542	-0.1763	-0.1763	-0.0305
	(0.5504)	(0.2395)	(0.2347)	(0.2601)
LABOR_FORCE	0.0681	-0.0572	0.5397	-0.2638
	(0.2185)	(0.5654)	(0.4474)	(0.2141)
Constant, Yr. & Ind. effects	Yes	Yes	Yes	Yes
Overall R-squared	0.6811	0.3416	0.6583	0.3215
N	1146	1712	1145	1710

Table B4 (Contd.)

Panel B. Number of bad loans as dependent variable

	Lower than median loan volume	Higher than median loan volume	Lower than median loan volume	Higher than median loan volume
Variables	**DV = BADLOANS COUNT**	**DV = BADLOANS COUNT**	**DV = BADLOANS COUNT**	**DV = BADLOANS COUNT**
AVEINTRATE			0.6442	1.5092*
			(0.4350)	(0.8380)
INFLATION	-0.0243	0.1782		
	(0.2549)	(0.2353)		
LOANVOLUME	0.1304***	0.1364***	0.1233***	0.0994***
	(0.0279)	(0.0329)	(0.0247)	(0.0284)
AVEDTI	-0.4781*	-0.3673	-0.5621**	-0.4411
	(0.2893)	(0.3701)	(0.2629)	(0.3565)
INTUSERS	0.0029	-0.0004	0.0016	-0.0013
	(0.0178)	(0.0089)	(0.0160)	(0.0095)
GDP_CONT	0.0808	0.0001	0.0829	-0.0054
	(0.0591)	(0.0646)	(0.0572)	(0.0673)
AVEINCOME	-0.1208	-2.8510	-0.1177	-4.1624
	(0.0967)	(3.3102)	(0.0969)	(2.8587)
NEW_BUS	0.2512	0.4797	0.2030	0.4937
	(0.3866)	(0.5350)	(0.3682)	(0.4518)
REPUBLICAN	0.5985***	-0.0321	0.5917***	-0.0386
	(0.2214)	(0.1412)	(0.2230)	(0.1356)
LABOR_FORCE	-0.4000	-0.1247	-0.4488	-0.1368
	(0.4689)	(0.1435)	(0.3878)	(0.1445)
Constant, Yr. & Ind. effects	Yes	Yes	Yes	Yes
Overall R-squared	0.0824	0.07210	0.0760	0.0836
N	1146	1712	1145	1710

Table B5: Impacts of average interest rate and inflation on bad loans (for subsamples of high and low religious states)

Table B5 presents the baseline regression results for two subsamples. Subsamples are drawn based on the religiosity of states. Median religiosity level is based on the variable of ‘Religiosity’. Refer to Table 1 for variable description. All model specifications employ robust standard errors in parentheses (* *p*<0.10, ** *p*<0.05, ****p*<0.01)

Panel A. Dollar value of bad loans as dependent variable

	High religiosity	**Low religiosity**	**High religiosity**	**Low religiosity**
	DV = BADLOANSVOL	**DV = BADLOANSVOL**	**DV = BADLOANSVOL**	**DV = BADLOANSVOL**
AVEINTRATE	0.9841***	0.5235***		
	(0.0957)	(0.0624)		
INFLATION			0.4448**	0.1734
			(0.1906)	(0.3696)
LOANVOLUME	0.5876***	0.8581***	0.3270***	0.6894***
	(0.0215)	(0.0562)	(0.0953)	(0.0698)
AVEDTI	0.1014***	0.0899***	0.0992***	0.0875***
	(0.0096)	(0.0220)	(0.0092)	(0.0256)
INTUSERS	-0.1443	-0.0816*	-0.1573*	-0.0704
	(0.0994)	(0.0461)	(0.0924)	(0.0430)
GDP_CONT	0.6814***	0.6736***	0.7174***	0.6734***
	(0.1861)	(0.0937)	(0.1690)	(0.0532)
AVEINCOME	0.2440	0.5642	0.2755	0.5749
	(0.6080)	(0.5092)	(0.5942)	(0.5477)
NEW_BUS	0.3001**	0.1818	0.3291**	0.1508
	(0.1431)	(0.1823)	(0.1370)	(0.1923)
REPUBLICAN	0.1242	-0.1015	0.0716	-0.0989
	(0.2697)	(0.3072)	(0.2282)	(0.3680)
Overall R-squared	0.4782	0.4007	0.4705	0.3938
N	1653	1205	1651	1204

Table B5 (Contd.)

	High religiosity	Low religiosity	High religiosity	Low religiosity
Panel B. Number of bad loans as dependent variable				
	DV = BADLOANS COUNT	**DV = BADLOANS COUNT**	**DV = BADLOANS COUNT**	**DV = BADLOANS COUNT**
AVEINTRATE	-0.7102**	-0.3530		
	(0.0793)	(0.6249)		
INFLATION			-0.0805	0.1085***
			(0.3413)	(0.2270)
LOANVOLUME	0.0041	-0.2392***	-0.0147	-0.2399***
	(0.0285)	(0.0707)	(0.0333)	(0.0426)
AVEDTI	-0.5751*	1.1004*	-0.7802**	1.0742**
	(0.3242)	(0.5919)	(0.3569)	(0.5320)
INTUSERS	0.0227	-0.0067	0.0190	-0.0080
	(0.0380)	(0.0167)	(0.0362)	(0.0145)
GDP_CONT	0.0431	-0.1290*	0.0506	-0.1327*
	(0.0942)	(0.0764)	(0.0915)	(0.0780)
AVEINCOME	-0.0016	-0.1825***	0.0103	-0.3243***
	(0.2246)	(0.0092)	(0.2155)	(0.0480)
NEW_BUS	0.4601	-0.1980	0.3098	-0.3137
	(0.8858)	(0.5082)	(0.9053)	(0.4156)
REPUBLICAN	0.0067	-0.1826	-0.0139	-0.1867
	(0.2697)	(0.3072)	(0.2282)	(0.3680)
Overall R-squared	0.4964	0.4248	0.4306	0.4264
N	1653	1205	1651	1204

Table B6: Impact of inflation and average interest rate on bad loans (robustness tests)

Table B6 presents the baseline regression results for three subsamples. Subsamples are formed by excluding several categories of observations. Sample 1 reports the results for the subsamples that exclude observations with high average revolving utilisation rates (higher than 0.45). Sample 2 reports the results for the subsamples that exclude high interest periods (periods with Federal Reserve target interest rate higher than 200 basis points). Sample3 reports the results for the subsamples that exclude three large states in terms of real GDP (California, Texas and New York). All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01)

Panel A.

Sample 1. Excluding observations with high average revolving utilisation rates

Variables	DV = badloans	DV = badloans
INFLATION	0.3448*	
	(0.1881)	
AVEINTRATE		-0.4522
		(0.5808)
Controls	Yes	Yes
Constant, Yr. & Ind. effects	Yes	Yes
Overall R-squared	0.3669	0.3491
N	1195	1195

Sample 2. Excluding observations with high interest rate

Variables	DV = badloans	DV = badloans
INFLATION	0.3350**	
	(0.1664)	
AVEINTRATE		-0.0903
		(0.3803)
Controls	Yes	Yes
Constant, Yr. & Ind. effects	Yes	Yes
Overall R-squared	0.3697	0.3552
N	1252	1252

Sample 3. Excluding observations for three large states

Variables	DV = badloans	DV = badloans
INFLATION	0.3300**	
	(0.1653)	
AVEINTRATE		-0.0819
		(0.4343)
Controls	Yes	Yes
Constant, Yr. & Ind. effects	Yes	Yes
Overall R-squared	0.3690	0.3540
N	1174	1174

Table B6 (Contd.)

Panel B.

Sample 1. Excluding observations with high average revolving utilisation rates

Variables	**DV = Badloans (Dummy)**	**DV = Badloans (Dummy)**
INFLATION	0.8723*** (0.0891)	
AVEINTRATE		-0.4522 (0.5808)
Controls	Yes	Yes
Constant, Yr. & Ind. effects	Yes	Yes
Overall R-squared	0.3304	0.3412
N	1195	1195

Sample 2. Excluding observations with high interest rate

Variables	**DV = Badloans (Dummy)**	**DV = Badloans (Dummy)**
INFLATION	0.9869*** (0.0840)	
AVEINTRATE		-0.2875*** (0.0266)
Controls	Yes	Yes
Constant, Yr. & Ind. effects	Yes	Yes
Overall R-squared	0.3051	0.3375
N	1252	1252

Sample 3. Excluding observations for three large states

Variables	**DV = Badloans (Dummy)**	**DV = Badloans (Dummy)**
INFLATION	0.9885*** (0.0839)	
AVEINTRATE		-0.2831*** (0.0265)
Controls	Yes	Yes
Constant, Yr. & Ind. effects	Yes	Yes
Overall R-squared	0.3091	0.3169
N	1174	1174

Table B7: Average interest rate and likelihood of loan default (RE estimation)

Table 5.7 reports the results for the Random Effects panel data estimation representing the effect of platform-specific variable (average interest rate) on the probability of default with control variables. Estimations are based on equation [8]. Estimation model employs the proportion of bad loans to total loans (PD) as the dependent variable. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

	Model 1	Model 2	Model 3	Model 4
Variables	**DV= PD**	**DV= PD**	**DV= PD**	**DV= PD**
AVEINTRATE	0.8547***	0.9059***	0.8685***	0.8565***
	(0.2326)	(0.2341)	(0.2339)	(0.2385)
LOANVOLUME	0.2014***	0.2007***	0.1989***	0.1701***
	(0.0458)	(0.0467)	(0.0467)	(0.0491)
AVEDTI	0.3961***	0.4832***	0.4535***	0.4668***
	(0.0474)	(0.0963)	(0.0535)	(0.0263)
INTUSERS	0.0914***	0.0961***	0.0962***	0.0970***
	(0.0083)	(0.0085)	(0.0079)	(0.0091)
GDP_CONT	0.0181	0.0176	0.0135	0.0138
	(0.0200)	(0.0200)	(0.0200)	(0.0201)
AVEINCOME	0.4042*	0.3932*	0.2357	0.2397
	(0.2079)	(0.2080)	(0.2104)	(0.2109)
NEW_BUS		0.2891*	0.3097**	0.3148**
		(0.1480)	(0.1486)	(0.1499)
REPUBLICAN			-0.0765	-0.0801
			(0.0622)	(0.0637)
LABOR_FORCE				-0.2649
				(1.0159)
Constant, Yr. & Ind. Effects	Yes	Yes	Yes	Yes
Overall R-squared	0.0388	0.0413	0.0422	0.0406
N	3223	3121	3121	2855

Table B8: Inflation and likelihood of loan default (RE estimation)

Table 5.8 reports the results for the Random Effects panel data estimation representing the effect of platform-specific variable (average interest rate) on probability of default with control variables. Estimations are based on equation [9]. Estimation model employs the proportion of bad loans to total loans (PD) as the dependent variable. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

	Model 1	**Model 2**	**Model 3**	**Model 4**
Variables	**DV= PD**	**DV= PD**	**DV= PD**	**DV= PD**
INFLATION	0.1736**	0.1751**	0.1685**	0.1686**
	(0.0697)	(0.0697)	(0.0698)	(0.0700)
LOANVOLUME	0.2342***	0.2310***	0.2290***	0.2035***
	(0.0452)	(0.0461)	(0.0461)	(0.0484)
AVEDTI	0.2553*	0.2628*	0.2970**	0.2972**
	(0.1391)	(0.1392)	(0.1397)	(0.1399)
INTUSERS	0.0932***	0.0978***	0.0980***	0.0991***
	(0.0077)	(0.0084)	(0.0082)	(0.0097)
GDP_CONT	0.0170	0.0168	0.0122	0.0121
	(0.0200)	(0.0200)	(0.0201)	(0.0201)
AVEINCOME	0.4552**	0.4450**	0.2807	0.2803
	(0.2090)	(0.2091)	(0.2118)	(0.2122)
NEW_BUS		0.2167	0.2476*	0.2468*
		(0.1476)	(0.1480)	(0.1496)
REPUBLICAN			-0.0519	-0.0514
			(0.0629)	(0.0644)
LABOR_FORCE				0.0341
				(1.0219)
Constant, Yr. & Ind. effects	Yes	Yes	Yes	Yes
Overall R-squared	0.0422	0.0429	0.0431	0.0425
N	3227	3124	3124	2858

Appendix C: Results of additional regression analyses for Chapter 7

Table C1: COVID-19 and the likelihood of late payments in the loan listings

Table C1 presents the results of probit regression analysis for the likelihood of late payments (STATUS_DUMMY) of listed loans. Number of listings analysed: 5,386,928. Current: 3,103,390 (57.61%). Late: 2,122,849(39.41%). Repaid: 160,689 (2.98%). Refer to Table 7.1 for the variable description. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

	(1)	(2)	(3)	(4)
	DV= STATUS_ DUMMY	**DV= STATUS_ DUMMY**	**DV= STATUS_ DUMMY**	**DV= STATUS_ DUMMY**
PANDEMIC_DUMMY	-0.1104*** (0.0093)			
CASES		0.0130*** (0.0023)		
DEATHS			-0.0411*** (0.0027)	
COVID_INDEX				0.0813*** (0.0054)
INDEX_CHANGE	0.0272*** (0.0027)	0.0678*** (0.0037)	0.0641*** (0.0036)	-0.0157*** (0.0025)
ESI	0.0264* (0.0159)	-0.1533*** (0.0199)	-0.3821*** (0.0239)	0.1903*** (0.0161)
POP	-0.0846*** (0.0032)	-0.0675*** (0.0058)	0.0484*** (0.0073)	-0.0983*** (0.0033)
RESTRUCTURED	-0.4620*** (0.0046)	-0.5007*** (0.0060)	-0.4996*** (0.0060)	-0.4616*** (0.0046)
AGE	-0.0065*** (0.0002)	-0.0057*** (0.0003)	-0.0057*** (0.0003)	-0.0065*** (0.0002)
GENDER	-0.2222*** (0.0030)	-0.2058*** (0.0034)	-0.2056*** (0.0034)	-0.2214*** (0.0030)
INTEREST	0.2898*** (0.0109)	0.2873*** (0.0133)	0.2807*** (0.0133)	0.2874*** (0.0109)
LOANDURATION	-0.0061*** (0.0002)	-0.0074*** (0.0002)	-0.0075*** (0.0002)	-0.0061*** (0.0002)
DTI	0.0006 (0.0005)	0.0005 (0.0007)	0.0007 (0.0007)	0.0005 (0.0005)
DISCOUNTRATE	-0.0001*** (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)
PRINCIPAL_DIFF	-0.0198*** (0.0005)	-0.0175*** (0.0006)	-0.0177*** (0.0006)	-0.0197*** (0.0005)
RATING				
A	-0.1552*** (0.0424)	-0.1796*** (0.0632)	-0.1791*** (0.0632)	-0.1556*** (0.0424)
B	-0.1866*** (0.0366)	-0.2704*** (0.0540)	-0.2690*** (0.0540)	-0.1853*** (0.0366)
C	-0.8909*** (0.0328)	-0.9230*** (0.0485)	-0.9183*** (0.0485)	-0.8921*** (0.0328)
D	-0.7210*** (0.0329)	-0.7799*** (0.0483)	-0.7687*** (0.0483)	-0.7221*** (0.0329)
E	-1.1946*** (0.0337)	-1.1765*** (0.0492)	-1.1667*** (0.0492)	-1.1951*** (0.0337)
F	-0.4144*** (0.0356)	-0.4977*** (0.0511)	-0.4832*** (0.0511)	-0.4125*** (0.0356)
HR	-0.1059*** (0.0376)	-0.1676*** (0.0534)	-0.1478*** (0.0534)	-0.1074*** (0.0376)

Table C1 (Contd.)

EMP_DUR				
Trial period	0.2175***	0.2242***	0.2250***	0.2168***
	(0.0090)	(0.0118)	(0.0118)	(0.0090)
Up to 1 year	0.3240***	0.3357***	0.3354***	0.3244***
	(0.0106)	(0.0140)	(0.0140)	(0.0106)
Up to 2 year	0.2049***	0.2338***	0.2325***	0.2022***
	(0.0618)	(0.0847)	(0.0847)	(0.0618)
Up to 3 year	0.2049***	0.2267***	0.2269***	0.2041***
	(0.0102)	(0.0133)	(0.0133)	(0.0102)
Up to 4 year	0.7188***	0.6940***	0.6937***	0.7169***
	(0.0239)	(0.0297)	(0.0297)	(0.0239)
Up to 5 year	0.7817***	0.7661***	0.7667***	0.7826***
	(0.0260)	(0.0325)	(0.0325)	(0.0260)
More than 5 years	0.5125***	0.5452***	0.5479***	0.5132***
	(0.0259)	(0.0328)	(0.0328)	(0.0259)
Retiree	0.2253***	0.2228***	0.2236***	0.2250***
	(0.0096)	(0.0125)	(0.0125)	(0.0096)
EDUCATION				
Primary education	-0.0002	0.0137	0.0129	-0.0013
	(0.0071)	(0.0091)	(0.0091)	(0.0071)
Basic education	0.5021***	0.5656***	0.5673***	0.4995***
	(0.0221)	(0.0295)	(0.0296)	(0.0221)
Vocational education	0.0274***	0.0516***	0.0514***	0.0263***
	(0.0056)	(0.0076)	(0.0076)	(0.0056)
Secondary education	0.0179***	0.0061	0.0064	0.0185***
	(0.0055)	(0.0066)	(0.0066)	(0.0055)
Higher education	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)
HOMEOWNERSHIP				
Owner	-0.1257***	-0.1335***	-0.1338***	-0.1278***
	(0.0083)	(0.0104)	(0.0104)	(0.0083)
Living with parents	0.1218***	0.1195***	0.1190***	0.1179***
	(0.0100)	(0.0117)	(0.0117)	(0.0100)
Tenant, pre-furnished property	0.0608***	0.0368***	0.0365***	0.0583***
	(0.0082)	(0.0103)	(0.0103)	(0.0083)
Tenant, unfurnished property	0.2873***	0.2559***	0.2552***	0.2878***
	(0.0189)	(0.0243)	(0.0243)	(0.0189)
Council house	0.2911***	0.2589***	0.2613***	0.2912***
	(0.0254)	(0.0324)	(0.0324)	(0.0254)
Joint tenant	0.4334***	0.3452***	0.3497***	0.4295***
	(0.0385)	(0.0478)	(0.0479)	(0.0385)
Joint ownership	0.5855***	0.6207***	0.6183***	0.5844***
	(0.0340)	(0.0435)	(0.0436)	(0.0341)
Mortgage	0.0265***	-0.0231**	-0.0222**	0.0251***
	(0.0089)	(0.0110)	(0.0110)	(0.0089)
Owner with encumbrance	0.0241	0.1434**	0.1423**	0.0227
	(0.0468)	(0.0600)	(0.0601)	(0.0468)
LR chi2	91475.6556	56478.4697	56682.4142	91557.8578
Prob > chi2	0.0000	0.0000	0.0000	0.0000
Pseudo-R-squared	0.1496	0.1488	0.1494	0.1497
N	5386928.0000	5386928.0000	5386928.0000	5386928.0000

Table C2: COVID-19 and the loan size

Table C2 presents the results of OLS regression analysis for the loan size (AMOUNT) of listed loans. Refer to Table 7.1 for the variable description. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

	(1)	(2)	(3)	(4)
	DV= AMOUNT	**DV= AMOUNT**	**DV= AMOUNT**	**DV= AMOUNT**
PANDEMIC_DUMMY	0.0149*** (0.0042)			
CASES		0.0043*** (0.0010)		
DEATHS			0.0069*** (0.0012)	
COVID_INDEX				-0.0061** (0.0024)
INDEX_CHANGE	-0.0064*** (0.0012)	-0.0110*** (0.0016)	-0.0082*** (0.0016)	-0.0020* (0.0011)
ESI	0.0472*** (0.0073)	0.0509*** (0.0089)	0.0804*** (0.0109)	0.0306*** (0.0074)
POP	-0.1740*** (0.0015)	-0.1796*** (0.0026)	-0.1874*** (0.0032)	-0.1728*** (0.0015)
RESTRUCTURED	0.0887*** (0.0022)	0.0814*** (0.0028)	0.0812*** (0.0028)	0.0887*** (0.0022)
AGE	0.0005*** (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0005*** (0.0001)
GENDER	0.0269*** (0.0013)	0.0270*** (0.0015)	0.0270*** (0.0015)	0.0269*** (0.0013)
INTEREST	-0.4165*** (0.0041)	-0.4280*** (0.0048)	-0.4276*** (0.0048)	-0.4162*** (0.0041)
LOANDURATION	0.0038*** (0.0001)	0.0030*** (0.0001)	0.0030*** (0.0001)	0.0038*** (0.0001)
DTI	0.0095*** (0.0002)	0.0105*** (0.0002)	0.0105*** (0.0002)	0.0095*** (0.0002)
DISCOUNTRATE	0.0000 (0.0000)	0.0000* (0.0000)	0.0000* (0.0000)	0.0000 (0.0000)
PRINCIPAL_DIFF	-0.0009*** (0.0002)	-0.0012*** (0.0002)	-0.0011*** (0.0002)	-0.0009*** (0.0002)
RATING				
A	-0.2581*** (0.0302)	-0.2635*** (0.0454)	-0.2635*** (0.0454)	-0.2581*** (0.0302)
B	0.2449*** (0.0249)	0.2233*** (0.0369)	0.2231*** (0.0369)	0.2447*** (0.0249)
C	0.5392*** (0.0216)	0.5293*** (0.0323)	0.5282*** (0.0323)	0.5394*** (0.0216)
D	0.8968*** (0.0213)	0.9059*** (0.0317)	0.9050*** (0.0317)	0.8969*** (0.0213)
E	0.9226*** (0.0214)	0.8936*** (0.0319)	0.8922*** (0.0319)	0.9227*** (0.0214)
F	1.2741*** (0.0218)	1.2334*** (0.0323)	1.2324*** (0.0323)	1.2739*** (0.0218)
HR	0.5316*** (0.0223)	0.4440*** (0.0329)	0.4425*** (0.0329)	0.5319*** (0.0223)
EMP_DUR				
Trial period	0.0461*** (0.0040)	0.0459*** (0.0051)	0.0459*** (0.0051)	0.0462*** (0.0040)
Up to 1 year	0.0979*** (0.0049)	0.0963*** (0.0063)	0.0963*** (0.0063)	0.0979*** (0.0049)

Table C2 (Contd.)

Up to 2 year	-0.1282***	-0.1158***	-0.1159***	-0.1280***
	(0.0328)	(0.0423)	(0.0423)	(0.0328)
Up to 3 year	0.0585***	0.0572***	0.0571***	0.0586***
	(0.0046)	(0.0058)	(0.0058)	(0.0046)
Up to 4 year	-0.0303***	-0.0254**	-0.0255**	-0.0302***
	(0.0093)	(0.0113)	(0.0113)	(0.0093)
Up to 5 year	0.0037	0.0650***	0.0650***	0.0037
	(0.0109)	(0.0138)	(0.0138)	(0.0109)
More than 5 years	0.0481***	0.0565***	0.0566***	0.0480***
	(0.0125)	(0.0156)	(0.0156)	(0.0125)
Retiree	0.0939***	0.0947***	0.0947***	0.0939***
	(0.0043)	(0.0054)	(0.0054)	(0.0043)
EDUCATION				
Primary education	0.3404**	0.1170	0.1157	0.3399**
	(0.1403)	(0.1222)	(0.1225)	(0.1409)
Basic education	0.1622	-0.0137	-0.0150	0.1619
	(0.1406)	(0.1227)	(0.1230)	(0.1412)
Vocational education	0.3422**	0.1235	0.1221	0.3417**
	(0.1403)	(0.1222)	(0.1225)	(0.1409)
Secondary education	0.2862**	0.0806	0.0794	0.2856**
	(0.1403)	(0.1222)	(0.1225)	(0.1409)
Higher education	0.3232**	0.1044	0.1031	0.3227**
	(0.1403)	(0.1222)	(0.1225)	(0.1409)
HOMEOWNERSHIP				
Owner	-0.5265**	-0.2087	-0.2072	-0.5256**
	(0.2211)	(0.2852)	(0.2861)	(0.2220)
Living with parents	-0.5626**	-0.2355	-0.2339	-0.5616**
	(0.2211)	(0.2853)	(0.2861)	(0.2220)
Tenant, pre-furnished property	-0.5091**	-0.1914	-0.1898	-0.5082**
	(0.2211)	(0.2852)	(0.2860)	(0.2220)
Tenant, unfurnished property	-0.6496***	-0.3550	-0.3529	-0.6491***
	(0.2212)	(0.2854)	(0.2862)	(0.2221)
Council house	-0.6516***	-0.3089	-0.3076	-0.6510***
	(0.2214)	(0.2856)	(0.2865)	(0.2223)
Joint tenant	-0.6800***	-0.3179	-0.3162	-0.6789***
	(0.2216)	(0.2858)	(0.2866)	(0.2225)
Joint ownership	-0.6867***	-0.3792	-0.3771	-0.6858***
	(0.2216)	(0.2859)	(0.2867)	(0.2226)
Mortgage	-0.5711***	-0.2510	-0.2493	-0.5703**
	(0.2211)	(0.2852)	(0.2861)	(0.2220)
Owner with encumbrance	-0.5574**	-0.2283	-0.2264	-0.5564**
	(0.2232)	(0.2878)	(0.2886)	(0.2241)
Pseudo-R-squared	0.3420	0.3920	0.3921	0.3420
N	5386928.0000	5386928.0000	5386928.0000	5386928.0000

Table C3: COVID-19 and the loan overdue days

Table C3 presents the results of OLS regression analysis for the loan overdue days (LATEDAYS) of listed loans. Refer to Table B3 for the variable description. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

	(1)	(2)	(3)	(4)
	DV= LATEDAYS	**DV= LATEDAYS**	**DV= LATEDAYS**	**DV= LATEDAYS**
PANDEMIC_DUMMY	0.0483*** (0.0159)			
CASES		0.0126*** (0.0038)		
DEATHS			-0.0795*** (0.0047)	
COVID_INDEX				0.3497*** (0.0091)
INDEX_CHANGE	0.0354*** (0.0047)	0.1539*** (0.0064)	0.1431*** (0.0063)	-0.0465*** (0.0043)
ESI	-0.4396*** (0.0283)	-0.9996*** (0.0347)	-1.4237*** (0.0413)	-0.0642** (0.0286)
POP	-0.3624*** (0.0059)	-0.2625*** (0.0103)	-0.0613*** (0.0130)	-0.4120*** (0.0060)
RESTRUCTURED	-0.6579*** (0.0081)	-0.6981*** (0.0105)	-0.6957*** (0.0105)	-0.6553*** (0.0081)
AGE	-0.0104*** (0.0004)	-0.0085*** (0.0005)	-0.0085*** (0.0005)	-0.0104*** (0.0004)
GENDER	-0.6333*** (0.0052)	-0.6127*** (0.0060)	-0.6118*** (0.0060)	-0.6298*** (0.0052)
INTEREST	0.8170*** (0.0160)	0.8091*** (0.0187)	0.8004*** (0.0187)	0.8069*** (0.0160)
LOANDURATION	-0.0181*** (0.0003)	-0.0197*** (0.0004)	-0.0198*** (0.0004)	-0.0180*** (0.0003)
DTI	-0.0104*** (0.0007)	-0.0125*** (0.0009)	-0.0123*** (0.0009)	-0.0105*** (0.0007)
DISCOUNTRATE	-0.0004** (0.0002)	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0004** (0.0002)
PRINCIPAL_DIFF	0.0001 (0.0006)	0.0045*** (0.0008)	0.0043*** (0.0008)	-0.0002 (0.0006)
RATING				
A	-0.5435*** (0.0923)	-0.6019*** (0.1376)	-0.6004*** (0.1379)	-0.5439*** (0.0919)
B	-0.6101*** (0.0796)	-0.9024*** (0.1186)	-0.8993*** (0.1188)	-0.6041*** (0.0792)
C	-2.5012*** (0.0705)	-2.5454*** (0.1049)	-2.5377*** (0.1051)	-2.4948*** (0.0702)
D	-2.2423*** (0.0701)	-2.3723*** (0.1038)	-2.3549*** (0.1040)	-2.2288*** (0.0697)
E	-3.4955*** (0.0709)	-3.4067*** (0.1047)	-3.3920*** (0.1049)	-3.4826*** (0.0705)
F	-1.5990*** (0.0730)	-1.7632*** (0.1067)	-1.7431*** (0.1069)	-1.5799*** (0.0726)
HR	-0.5529*** (0.0761)	-0.6330*** (0.1100)	-0.6050*** (0.1102)	-0.5418*** (0.0758)
EMP_DUR				
Trial period	0.5266*** (0.0141)	0.5072*** (0.0185)	0.5085*** (0.0184)	0.5246*** (0.0141)
Up to 1 year	0.4637*** (0.0170)	0.4559*** (0.0226)	0.4554*** (0.0226)	0.4635*** (0.0169)

Table C3 (Contd.)

Up to 2 year	0.5118***	0.7075***	0.7046***	0.5135***
	(0.0993)	(0.1238)	(0.1238)	(0.0995)
Up to 3 year	0.4505***	0.4327***	0.4327***	0.4473***
	(0.0161)	(0.0211)	(0.0210)	(0.0161)
Up to 4 year	1.4660***	1.3924***	1.3927***	1.4631***
	(0.0336)	(0.0414)	(0.0414)	(0.0336)
Up to 5 year	1.7180***	1.6838***	1.6839***	1.7194***
	(0.0363)	(0.0444)	(0.0443)	(0.0363)
More than 5 years	1.1069***	1.1019***	1.1034***	1.1038***
	(0.0412)	(0.0501)	(0.0501)	(0.0412)
Retiree	0.4094***	0.3815***	0.3826***	0.4084***
	(0.0153)	(0.0199)	(0.0199)	(0.0152)
EDUCATION				
Primary education	-0.1570	-0.5482*	-0.5405*	-0.1514
	(0.3596)	(0.3074)	(0.3037)	(0.3445)
Basic education	0.6787*	0.3611	0.3713	0.6821**
	(0.3608)	(0.3094)	(0.3057)	(0.3458)
Vocational education	0.0073	-0.3242	-0.3158	0.0129
	(0.3595)	(0.3073)	(0.3036)	(0.3444)
Secondary education	-0.0351	-0.4944	-0.4855	-0.0264
	(0.3595)	(0.3071)	(0.3035)	(0.3443)
Higher education	-0.0669	-0.4827	-0.4741	-0.0594
	(0.3595)	(0.3072)	(0.3035)	(0.3444)
HOMEOWNERSHIP				
Owner	-2.8154***	-1.8593***	-1.8976***	-2.8526***
	(0.5655)	(0.7058)	(0.7014)	(0.5428)
Living with parents	-2.3579***	-1.3850**	-1.4242**	-2.4006***
	(0.5656)	(0.7059)	(0.7016)	(0.5430)
Tenant, pre-furnished property	-2.4908***	-1.5566**	-1.5952**	-2.5293***
	(0.5654)	(0.7057)	(0.7013)	(0.5428)
Tenant, unfurnished property	-1.8466***	-0.9300	-0.9696	-1.8800***
	(0.5661)	(0.7066)	(0.7022)	(0.5435)
Council house	-1.3469**	-0.4200	-0.4536	-1.3799**
	(0.5673)	(0.7081)	(0.7037)	(0.5447)
Joint tenant	-1.2763**	-0.5488	-0.5819	-1.3240**
	(0.5678)	(0.7084)	(0.7040)	(0.5452)
Joint ownership	-1.4255**	-0.4431	-0.4872	-1.4672***
	(0.5677)	(0.7084)	(0.7041)	(0.5451)
Mortgage	-2.5089***	-1.6734**	-1.7098**	-2.5444***
	(0.5655)	(0.7058)	(0.7014)	(0.5428)
Owner with encumbrance	-2.3974***	-1.2718*	-1.3134*	-2.4282***
	(0.5757)	(0.7182)	(0.7138)	(0.5535)
Pseudo-R-squared	0.3266	0.3350	0.3357	0.3287
N	5386928.0000	5386928.0000	5386928.0000	5386928.0000

Table C4: COVID-19 and the likelihood of successful listing (by country)

Table C4 presents the results of probit regression analysis for the likelihood of successful listings (RESULT_DUMMY) based on three panels (by country of loan origination). All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01)

	(1)	(2)	(3)	(4)
Panel A: country of loan origination - Estonia				
Variables	**DV=RESULT_DUMMY**	**DV=RESULT_DUMMY**	**DV=RESULT_DUMMY**	**DV=RESULT_DUMMY**
PANDEMIC_DUMMY	0.8754*** (0.0090)			
CASES		0.0897*** (0.0011)		
DEATHS			0.2105*** (0.0020)	
COVID_INDEX				-0.4345*** (0.0032)
Controls				
LR chi2	31115.4137	28263.7565	34110.4730	44664.2187
Prob > chi2	0.0000	0.0000	0.0000	0.0000
Pseudo-R-squared	0.1204	0.1094	0.1320	0.1729
N	251557.0000	251557.0000	251557.0000	251557.0000
Panel B: country of loan origination - Finland				
Variables	**DV=RESULT_DUMMY**	**DV=RESULT_DUMMY**	**DV=RESULT_DUMMY**	**DV=RESULT_DUMMY**
PANDEMIC_DUMMY	0.7781*** (0.0031)			
CASES		-0.0078*** (0.0022)		
DEATHS			0.0377*** (0.0020)	
COVID_INDEX				-0.2265*** (0.0061)
Controls				
LR chi2	243002.6064	12653.7720	12997.5565	26607.5431
Prob > chi2	0.0000	0.0000	0.0000	0.0000
Pseudo-R-squared	0.1390	0.0697	0.0716	0.0776
N	1606869.0000	275584.0000	275584.0000	443345.0000
Panel C: country of loan origination - Spain				
Variables	**DV=RESULT_DUMMY**	**DV=RESULT_DUMMY**	**DV=RESULT_DUMMY**	**DV=RESULT_DUMMY**
PANDEMIC_DUMMY	1.0469*** (0.0073)			
CASES		0.2768*** (0.0022)		
DEATHS			0.0933*** (0.0056)	
COVID_INDEX				-0.2898*** (0.0100)
Controls				
LR chi2	85969.9896	80784.0078	22705.7859	23309.4439
Prob > chi2	0.0000	0.0000	0.0000	0.0000
Pseudo-R-squared	0.1799	0.1690	0.1116	0.1146
N	459926.0000	459926.0000	278033.0000	278033.0000

Table C5: COVID-19 and the likelihood of successful listing (by month)

Table C5 presents the results of probit regression analysis for the likelihood of successful listings (RESULT_DUMMY) based on 5 panels (by each month of listing date from February to June 2020). All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01)

	(1)	**(2)**	**(3)**
Panel A: date of listing - February			
Variables	**DV=RESULT_ DUMMY**	**DV=RESULT_ DUMMY**	**DV=RESULT_ DUMMY**
CASES	0.0942*** (0.0045)		
DEATHS		NA	
COVID_INDEX			-0.6777*** (0.0015)
Controls	Yes	Yes	Yes
LR chi2	36281.1170	36003.0718	333926.4393
Prob > chi2	0.0000	0.0000	0.0000
Pseudo-R-squared	0.0342	0.0340	0.3151
N	870052.0000	869811.0000	869811.0000
Panel B: date of listing - March			
Variables	**DV=RESULT_ DUMMY**	**DV=RESULT_ DUMMY**	**DV=RESULT_ DUMMY**
CASES	0.2014*** (0.0008)		
DEATHS		0.1887*** (0.0014)	
COVID_INDEX			-0.0737*** (0.0013)
Controls	Yes	Yes	Yes
LR chi2	95770.1998	60220.8402	42531.0050
Prob > chi2	0.0000	0.0000	0.0000
Pseudo-R-squared	0.0610	0.0384	0.0271
N	1849019.0000	1848859.0000	1848859.0000
Panel C: date of listing - April			
Variables	**DV=RESULT_ DUMMY**	**DV=RESULT_ DUMMY**	**DV=RESULT_ DUMMY**
CASES	0.0907*** (0.0019)		
DEATHS		0.0280*** (0.0022)	
COVID_INDEX			2.2216*** (0.0131)
Controls	Yes	Yes	Yes
LR chi2	25916.0629	23949.5284	52807.1045
Prob > chi2	0.0000	0.0000	0.0000
Pseudo-R-squared	0.0359	0.0332	0.0731
N	819065.0000	818998.0000	818998.0000

Table C5 (Contd.)

Panel D: date of listing - May			
Variables	**DV=RESULT_ DUMMY**	**DV=RESULT_ DUMMY**	**DV=RESULT_ DUMMY**
CASES	-0.0040 (0.0027)		
DEATHS		-0.0737*** (0.0032)	
COVID_INDEX			1.4124*** (0.0125)
Controls	Yes	Yes	Yes
LR chi2	22596.8366	23346.2704	36127.0924
Prob > chi2	0.0000	0.0000	0.0000
Pseudo-R-squared	0.0464	0.0479	0.0742
N	478117.0000	478069.0000	478069.0000
Panel E: date of listing - June			
Variables	**DV=RESULT_ DUMMY**	**DV=RESULT_ DUMMY**	**DV=RESULT_ DUMMY**
CASES	-0.0178*** (0.0029)		
DEATHS		-0.2363*** (0.0144)	
COVID_INDEX			0.0243*** (0.0075)
Controls	Yes	Yes	Yes
LR chi2	7447.4771	7961.7495	7715.0777
Prob > chi2	0.0000	0.0000	0.0000
Pseudo-R-squared	0.0352	0.0377	0.0365
N	251816.0000	251779.0000	251779.0000

Appendix D: Snapshot of the database before and after aggregation (Chapter 5)

Figure D1. Snapshot of the database before aggregation

int_rate	annual_inc	issue_d	loan_status	addr_state	dti	revol_util
13.58%	51738	Mar-18	Current	OR	6.87	37.80%
6.07%	240000	Mar-18	Current	CT	10.99	22.10%
9.43%	85000	Mar-18	Current	GA	9.12	17.80%
7.96%	42000	Mar-18	Current	NY	6.94	31.30%
7.34%	100000	Mar-18	Current	WA	24.95	47.70%
12.61%	450000	Mar-18	Current	NJ	7.61	82.60%
7.34%	180700	Mar-18	Current	IL	18.98	36.90%
24.84%	45700	Mar-18	Current	CA	31.36	66.30%
11.98%	55000	Mar-18	Fully Paid	GA	14.18	33.90%
10.41%	110000	Mar-18	Current	CA	11.48	45.90%
9.43%	48000	Mar-18	Current	CA	7.88	34.90%
13.58%	82985	Mar-18	Current	NJ	18.66	35.10%
6.71%	60000	Mar-18	Current	OH	1.36	21.80%
7.96%	82000	Mar-18	Current	GA	24.53	69.50%
10.90%	57000	Mar-18	Current	AZ	21.81	48.30%

Figure D2. Snapshot of the database after aggregation

state_abre	date	loanvolume	loancount	aveintrate	aveincome	avedti	averevol
WA	1-Oct-15	15300000	975	0.1223255	78460.24	0.1884644	0.5609918
WA	1-Nov-15	11500000	753	0.1231809	79070.02	0.1908773	0.5508192
WA	1-Dec-15	13500000	878	0.1252271	77607.2	0.1954859	0.5607984
WA	1-Jan-16	11000000	658	0.1207467	82485.71	0.1884571	0.5497219
WA	1-Feb-16	12800000	812	0.1239884	81875.69	0.199636	0.5617509
WA	1-Mar-16	19500000	1240	0.1269878	77473.59	0.1930235	0.5415921
WA	1-Apr-16	11000000	722	0.1259414	77107.34	0.183106	0.5312022
WA	1-May-16	8356425	549	0.1238188	78166.81	0.192237	0.5310439
WA	1-Jun-16	9697200	645	0.1224912	81274.25	0.1767616	0.5098016
WA	1-Jul-16	9035800	643	0.1354185	76848.89	0.1746554	0.5380793
WA	1-Aug-16	9295500	644	0.1376455	76712.33	0.1773179	0.5409891
WA	1-Sep-16	7326150	515	0.1380384	76988.56	0.1758505	0.5152563
WA	1-Oct-16	9957025	667	0.1345051	82789.46	0.1924478	0.5388741
WA	1-Nov-16	8296675	593	0.1355271	79821.63	0.3517777	0.5537618
WA	1-Dec-16	9107475	613	0.1403819	83406.85	0.3512755	0.5329739
WA	1-Jan-17	1.05E+07	714	0.1314043	81200.25	0.1851289	0.5415154